# Bilateral Filters

Digital Visual Effects

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*with slides by Fredo Durand, Ramesh Raskar, Sylvain Paris, Soonmin Bae*

## Bilateral filtering


[Ben Weiss, Siggraph 2006]

## Image Denoising

noisy image | naïve denoising Gaussian blur | better denoising edge-preserving filter

Smoothing an image without blurring its edges.

## A Wide Range of Options

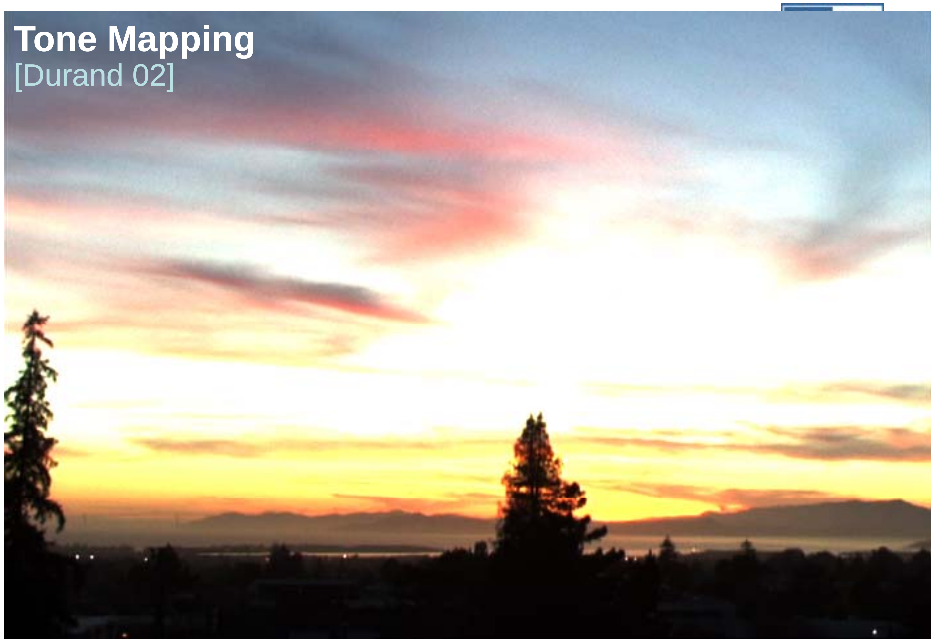
- Diffusion, Bayesian, Wavelets…
  - All have their pros and cons.
- Bilateral filter
  - not always the best result [Buades 05] but often good
  - easy to understand, adapt and set up

## Basic denoising

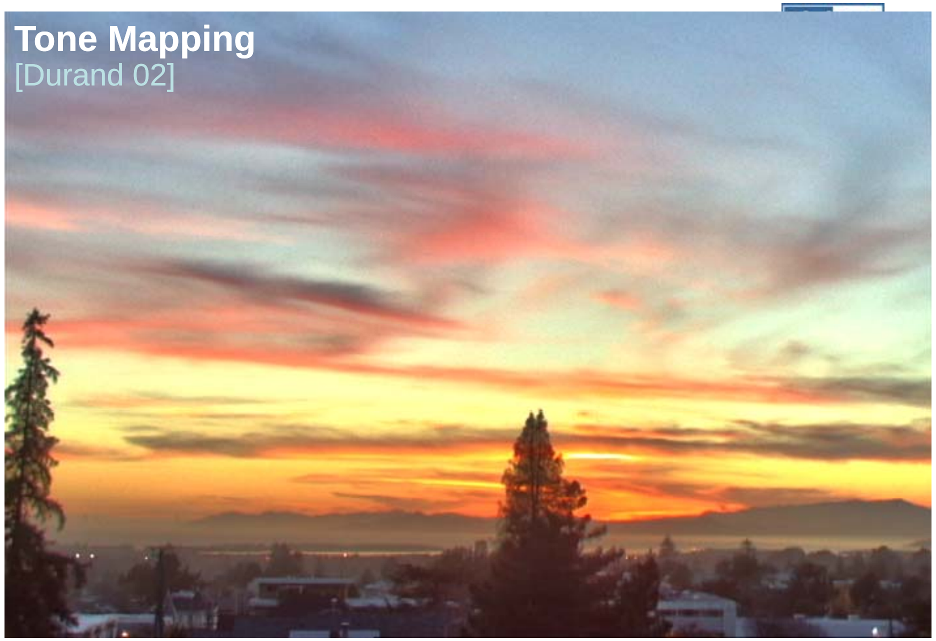
Noisy input | Median 5x5

## Basic denoising

Noisy input | Bilateral filter 7x7 window




HDR input

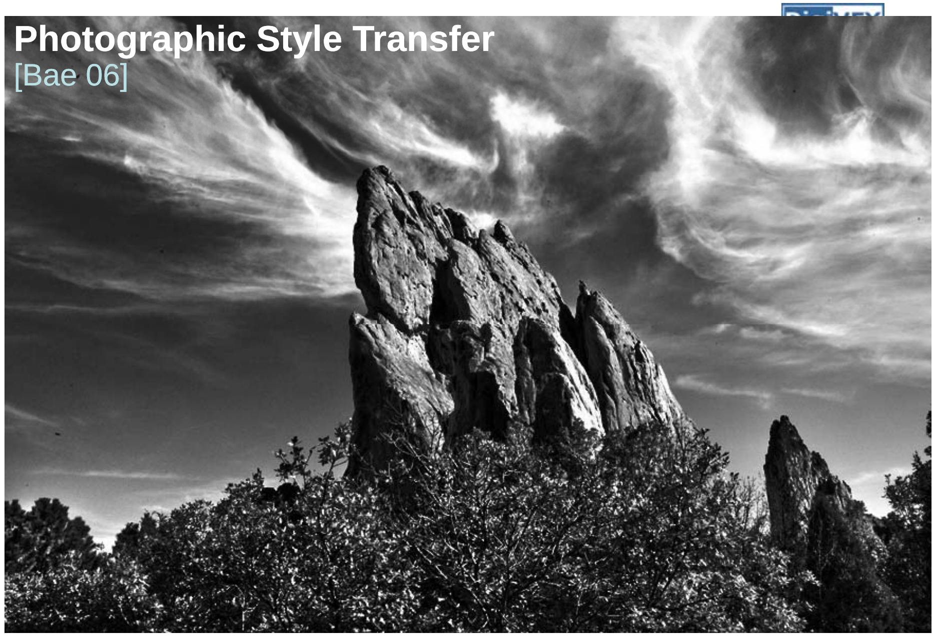



output

## Photographic Style Transfer
[Bae 06]

input

## Photographic Style Transfer
[Bae 06]

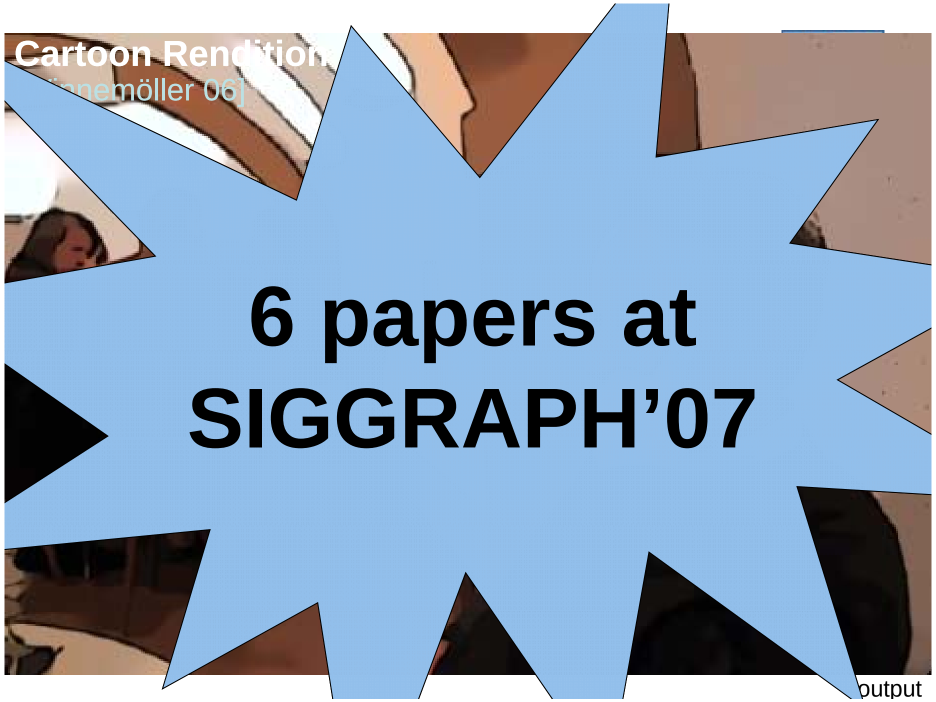


output

## Cartoon Rendition
[Winnemöller 06]

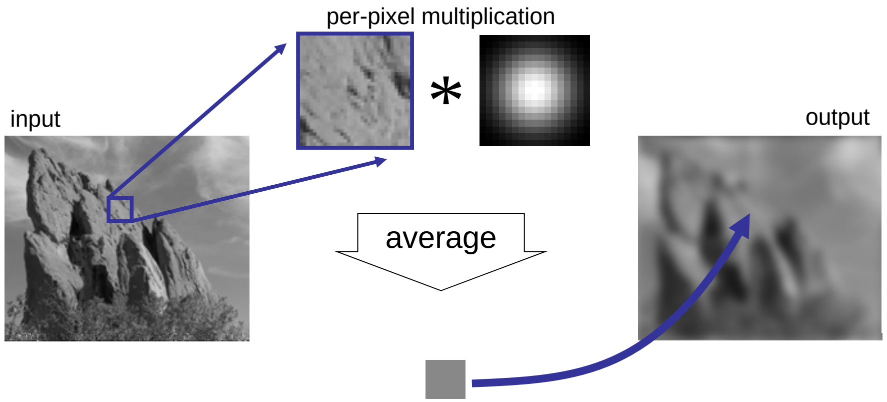
input

## Cartoon Rendition
[Winnemöller 06]




output

# Gaussian Blur



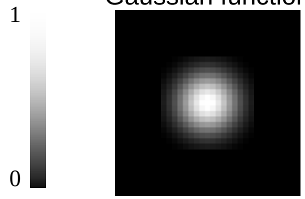



## Equation of Gaussian Blur

Same idea: **weighted average of pixels**.

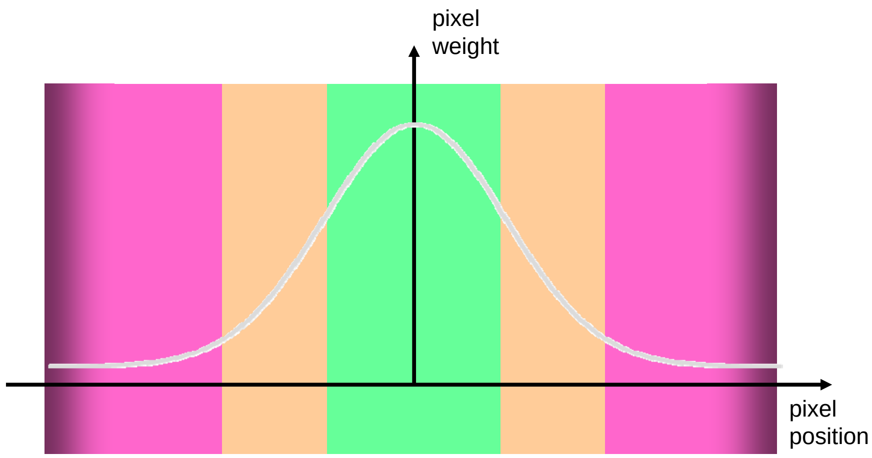
$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q} \in S} G_\sigma(\|\mathbf{p}-\mathbf{q}\|)\, I_{\mathbf{q}}$$

normalized Gaussian function




## Gaussian Profile

$$G_\sigma(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$

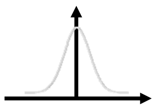



## Spatial Parameter

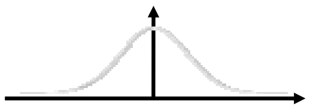
input

$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q} \in S} G_\sigma(\|\mathbf{p}-\mathbf{q}\|)\, I_{\mathbf{q}}$$

size of the window

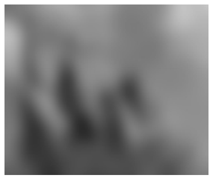


small $\sigma$



large $\sigma$

limited smoothing



strong smoothing

## How to set $\sigma$

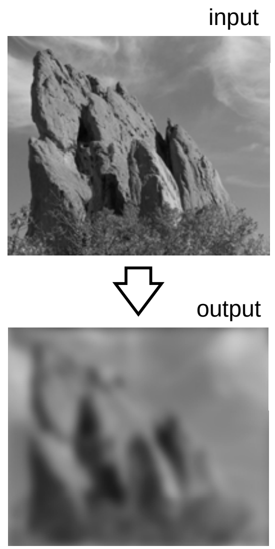
- Depends on the application.
- Common strategy: proportional to image size
  - e.g. 2% of the image diagonal
  - property: independent of image resolution

## Properties of Gaussian Blur

- Weights independent of spatial location
  - linear convolution
  - well-known operation
  - efficient computation (recursive algorithm, FFT…)

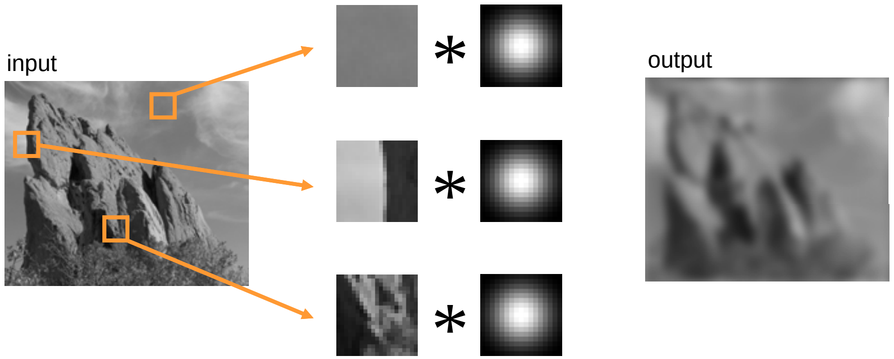
## Properties of Gaussian Blur

- Does smooth images
- But smoothes too much: **edges are blurred.**
  - Only spatial distance matters
  - No edge term




$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q}\in S} \underbrace{G_\sigma(\|\mathbf{p}-\mathbf{q}\|)}_{\text{space}} I_{\mathbf{q}}$$

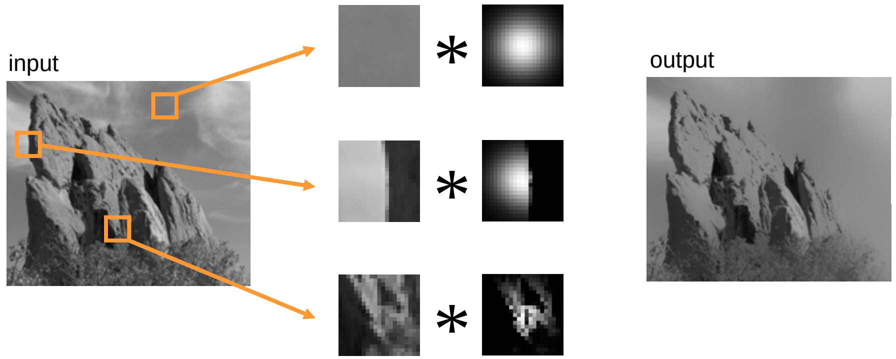
## Blur Comes from Averaging across Edges




Same Gaussian kernel everywhere.

## Bilateral Filter No Averaging across Edges

[Aurich 95, Smith 97, Tomasi 98]




The kernel shape depends on the image content.

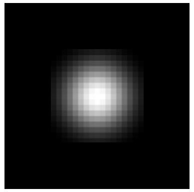
## Bilateral Filter Definition

Same idea: **weighted average of pixels**.

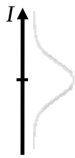
$$BF[I]_{\mathbf{p}} = \underbrace{\frac{1}{W_{\mathbf{p}}}}_{\text{new}} \sum_{\mathbf{q}\in S} \underbrace{G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)}_{\text{not new}} \underbrace{G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)}_{\text{new}} I_{\mathbf{q}}$$

normalization factor

***space*** weight



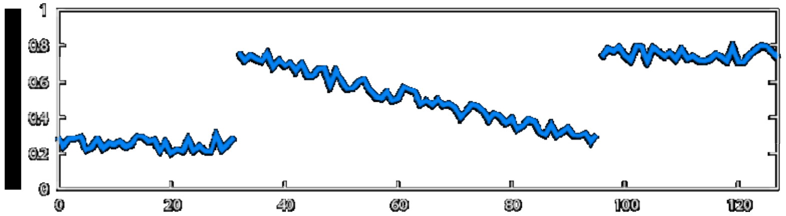
***range*** weight




## Illustration a 1D Image

- 1D image = line of pixels

- Better visualized as a plot

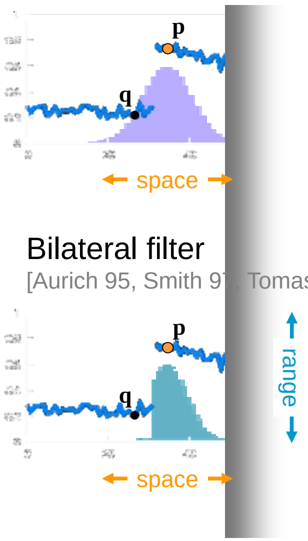



## Gaussian Blur and Bilateral Filter

Gaussian blur

Bilateral filter

[Aurich 95, Smith 97, Tomasi 98]




$$GB[I]_{\mathbf{p}} = \sum_{\mathbf{q}\in S} G_{\sigma}(\|\mathbf{p}-\mathbf{q}\|) I_{\mathbf{q}}$$

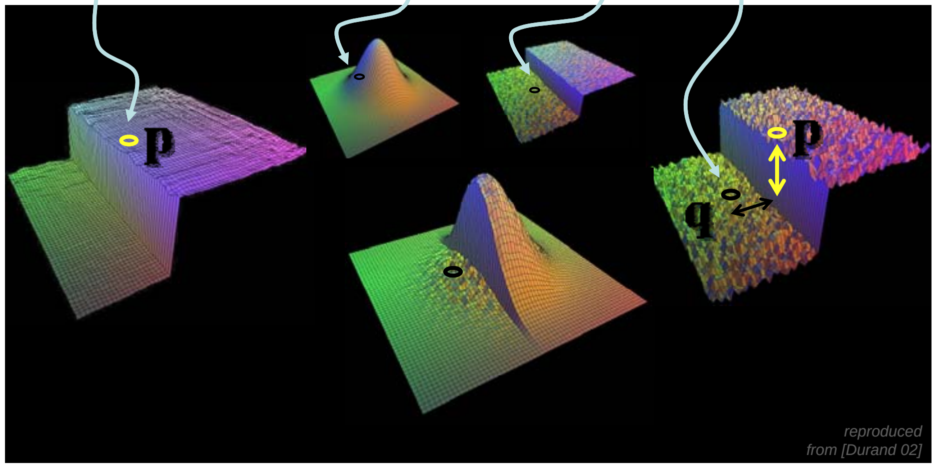
space

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in S} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|) G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|) I_{\mathbf{q}}$$

normalization — space — range

## Bilateral Filter on a Height Field

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in S} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\ G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)\ I_{\mathbf{q}}$$



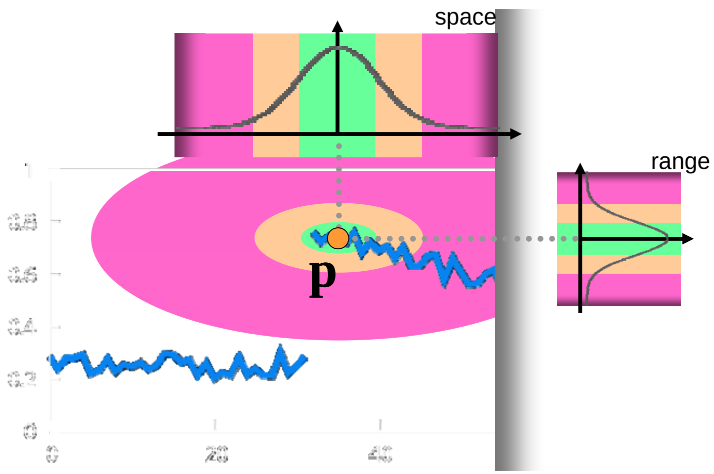
## Space and Range Parameters

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\, G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)\, I_{\mathbf{q}}$$

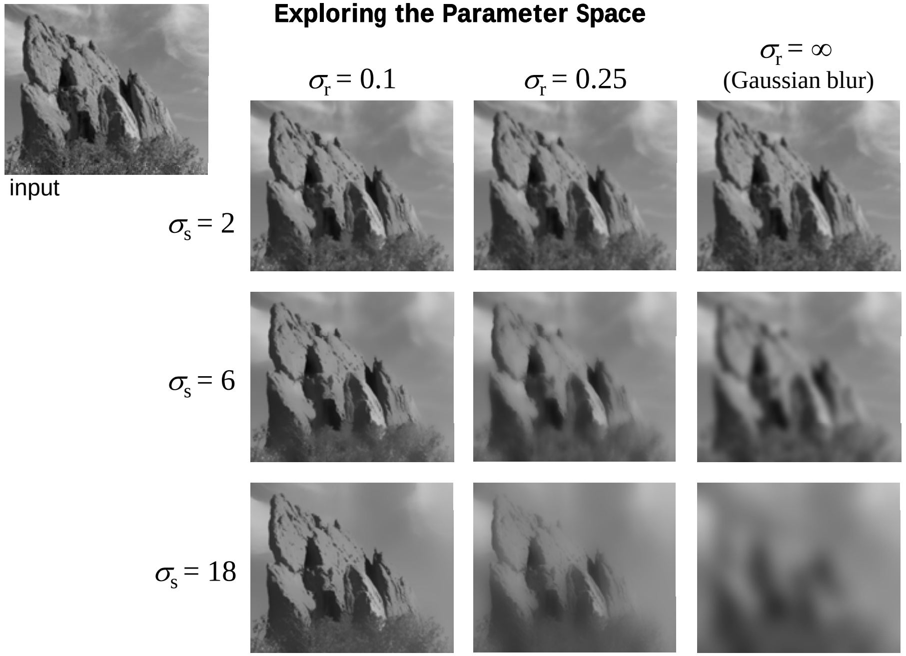
- space $\sigma_s$ : spatial extent of the kernel, size of the considered neighborhood.
- range $\sigma_r$ : "minimum" amplitude of an edge

## Influence of Pixels

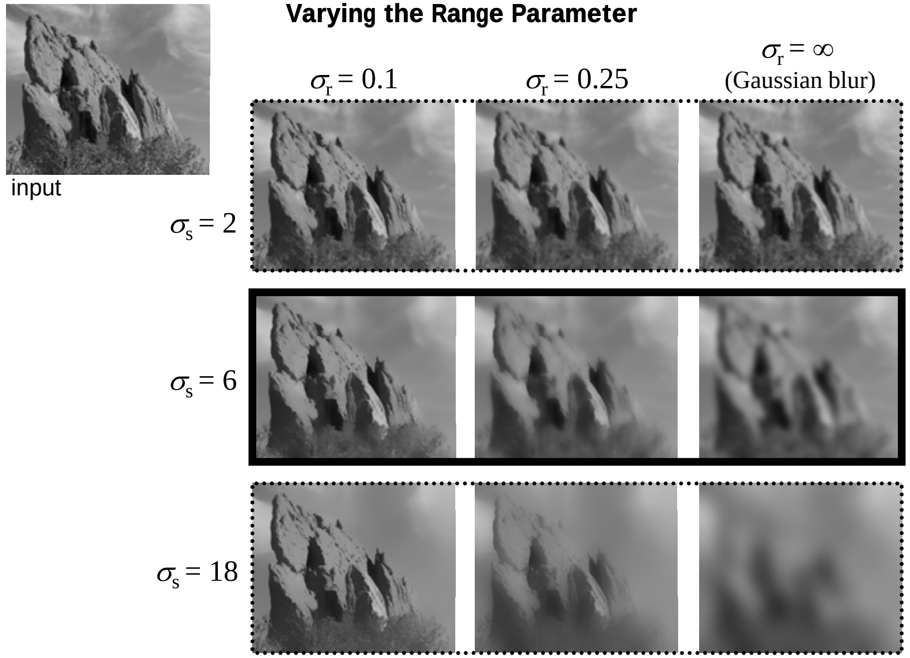
Only pixels close in space and in range are considered.




### Exploring the Parameter Space

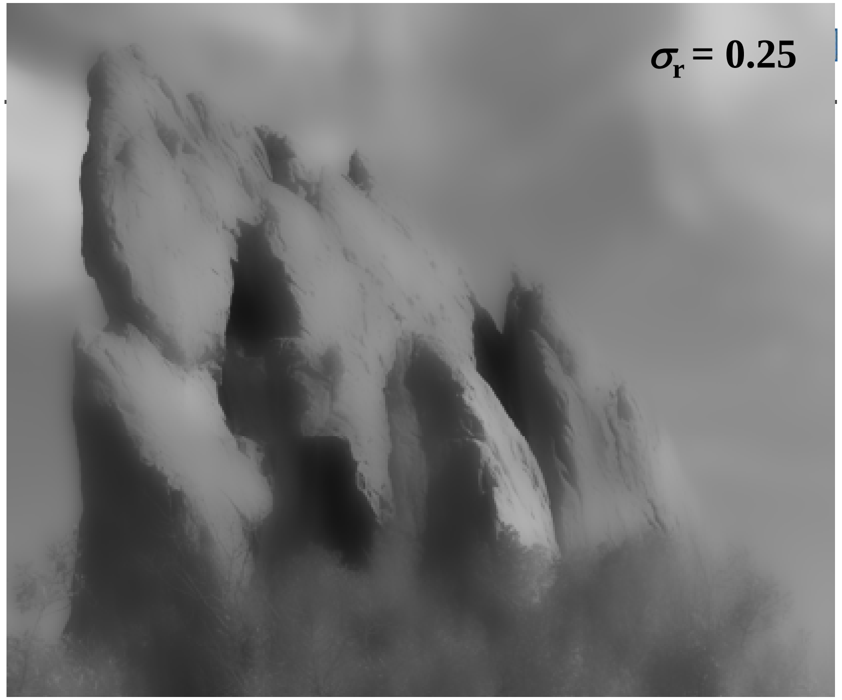



### Varying the Range Parameter



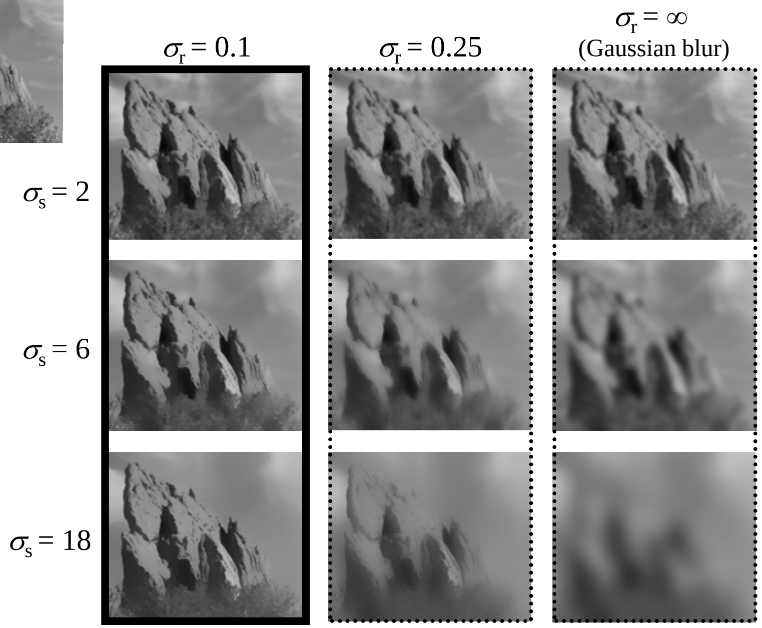

input


$\sigma_r = 0.1$


$\sigma_r = 0.25$


$\sigma_r = \infty$
(Gaussian blur)

## Varying the Space Parameter





# How to Set the Parameters

Depends on the application. For instance:

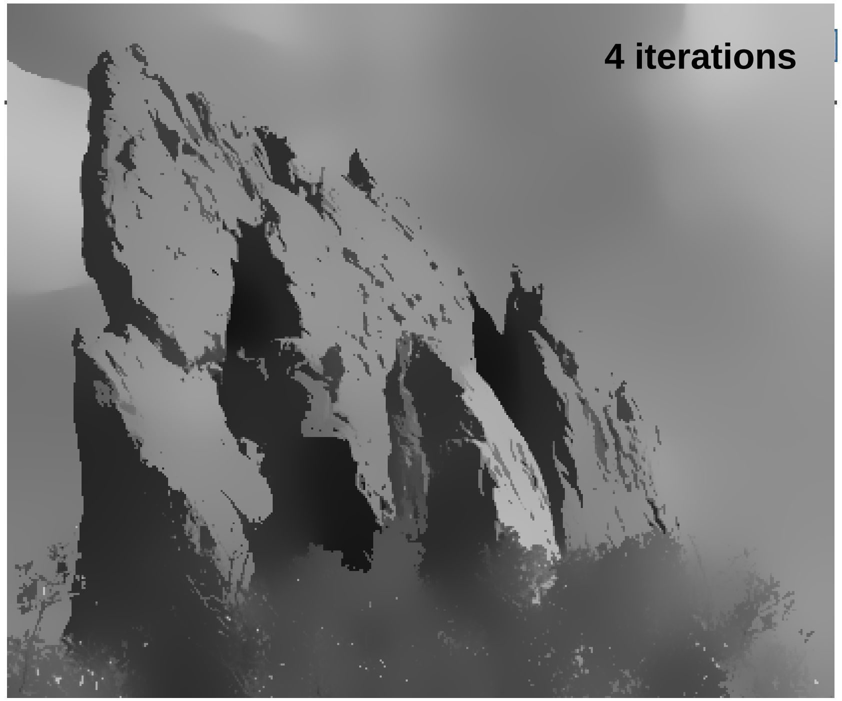
- space parameter: proportional to image size
  - e.g., 2% of image diagonal
- range parameter: proportional to edge amplitude
  - e.g., mean or median of image gradients
- independent of resolution and exposure

# Iterating the Bilateral Filter

$$I_{(n+1)} = BF[I_{(n)}]$$

- Generate more piecewise-flat images
- Often not needed in computational photo, but could be useful for applications such as NPR.






## Advantages of Bilateral Filter

DigiVFX

- Easy to understand
  - Weighted mean of nearby pixels
- Easy to adapt
  - Distance between pixel values
- Easy to set up
  - Non-iterative

## Hard to Compute

- Nonlinear $BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|) G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|) I_{\mathbf{q}}$
- Complex, spatially varying kernels
  - Cannot be precomputed, no FFT…

- Brute-force implementation is slow > 10min

## But Bilateral Filter is Nonlinear

- Slow but some accelerations exist:
  - [Elad 02]: Gauss-Seidel iterations
    - **Only for many iterations**
  - [Durand 02, Weiss 06]: fast approximation
    - **No formal understanding** of accuracy versus speed
    - [Weiss 06]: Only **box function** as spatial kernel

# A Fast Approximation of the Bilateral Filter using a Signal Processing Approach

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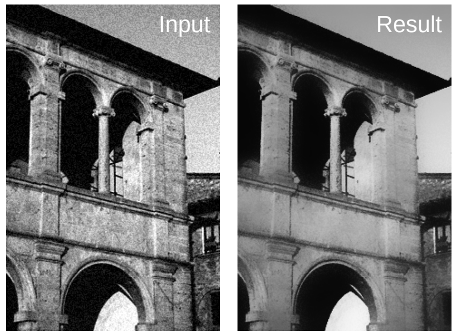
Computer Science and Artificial Intelligence Laboratory
Massachusetts Institute of Technology

## Definition of Bilateral Filter

- [Smith 97, Tomasi 98]
- Smoothes an image and preserves edges
- Weighted average of neighbors
- Weights
  - Gaussian on *space* distance
  - Gaussian on *range* distance
  - sum to 1

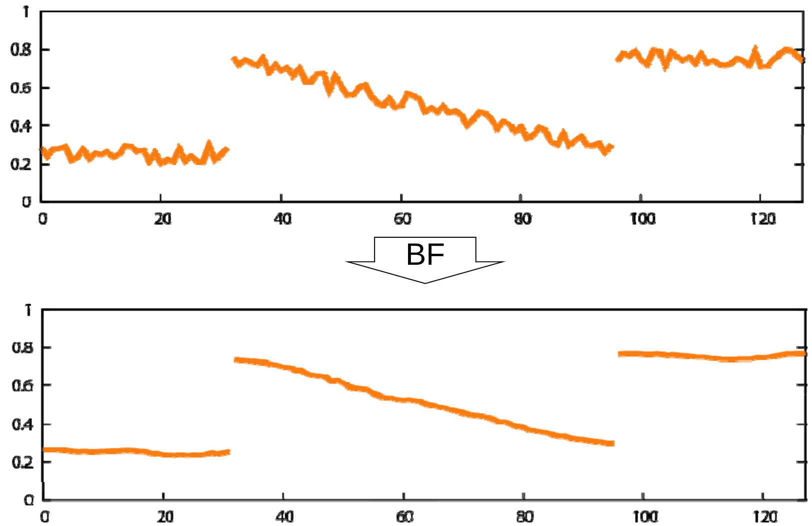



$$I_{\mathbf{p}}^{\mathrm{bf}} = \frac{1}{W_{\mathbf{p}}^{\mathrm{bf}}} \sum_{\mathbf{q} \in \mathcal{S}} \underbrace{G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)}_{\text{space}} \underbrace{G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)}_{\text{range}} I_{\mathbf{q}}$$

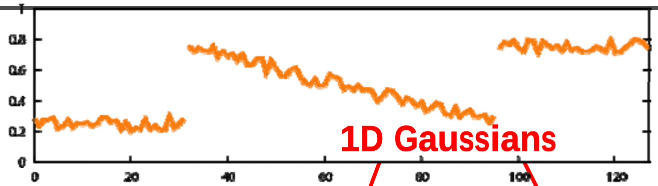
## Contributions

- Link with **linear filtering**
- **Fast** and **accurate** approximation

## Intuition on 1D Signal



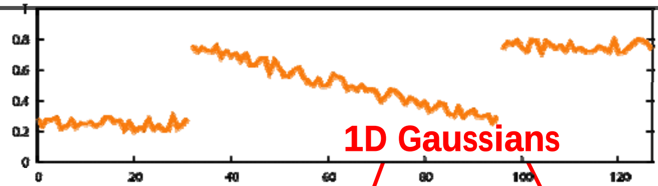

## Basic idea



1D Gaussians

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in S} G(\mathbf{q};\mathbf{p},\sigma_s)\, G(I_{\mathbf{q}};I_{\mathbf{p}},\sigma_r)\, I_{\mathbf{q}}$$

## Basic idea



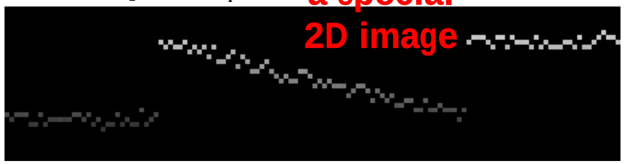
1D Gaussians

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q}\in S} G(\mathbf{q};\mathbf{p},\sigma_s)\, G(I_{\mathbf{q}};I_{\mathbf{p}},\sigma_r)\, I_{\mathbf{q}}$$

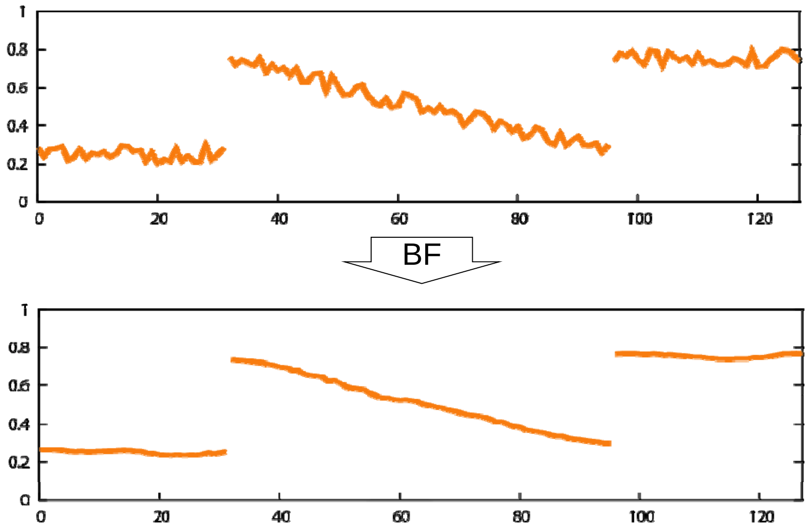
2D Gaussians

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\langle\mathbf{q},I'_{\mathbf{q}}\rangle\in S'} G(\mathbf{q},I_{\mathbf{q}};\mathbf{p},I_{\mathbf{p}},\sigma_s,\sigma_r)\, I_{\langle\mathbf{q},I'_{\mathbf{q}}\rangle}$$

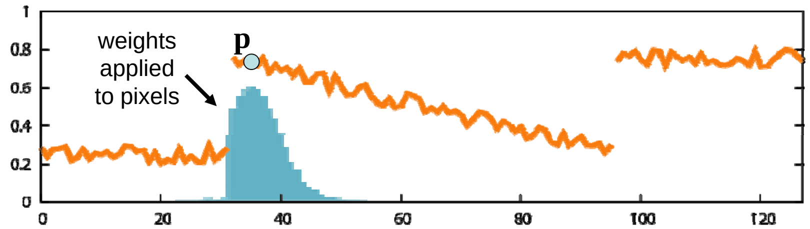
a special 2D image



## Intuition on 1D Signal

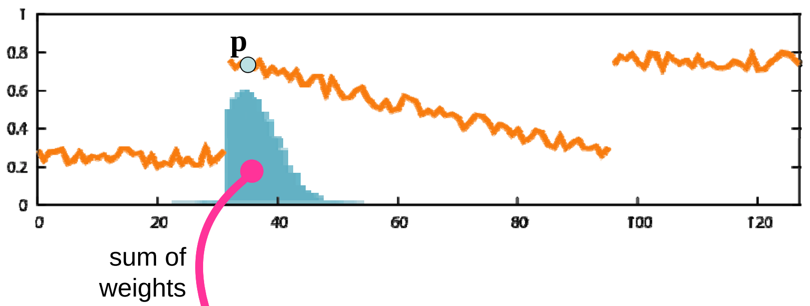



## Intuition on 1D Signal
### Weighted Average of Neighbors




- Near and similar pixels have influence.
- Far pixels have no influence.
- Pixels with different value have no influence.

## Link with Linear Filtering
### 1. Handling the Division




$$I^{bf}_{\mathbf{p}} = \frac{1}{W^{bf}_{\mathbf{p}}} \sum_{\mathbf{q}\in\mathcal{S}} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\, G_{\sigma_r}(|I_{\mathbf{p}}-I_{\mathbf{q}}|)\, I_{\mathbf{q}}$$

Handling the division with a **projective space**.

## Formalization: Handling the Division

$$I^{bf}_{\mathbf{p}} = \frac{1}{W^{bf}_{\mathbf{p}}} \sum_{\mathbf{q}\in\mathcal{S}} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\, G_{\sigma_r}(|I_{\mathbf{p}}-I_{\mathbf{q}}|)\, I_{\mathbf{q}}$$

$$W^{bf}_{\mathbf{p}} = \sum_{\mathbf{q}\in\mathcal{S}} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\, G_{\sigma_r}(|I_{\mathbf{p}}-I_{\mathbf{q}}|)$$

- Normalizing factor as homogeneous coordinate
  - Multiply both sides by $W^{bf}_{\mathbf{p}}$

$$\begin{pmatrix} W^{bf}_{\mathbf{p}} I^{bf}_{\mathbf{p}} \\ W^{bf}_{\mathbf{p}} \end{pmatrix} = \sum_{\mathbf{q}\in\mathcal{S}} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\, G_{\sigma_r}(|I_{\mathbf{p}}-I_{\mathbf{q}}|) \begin{pmatrix} I_{\mathbf{q}} \\ 1 \end{pmatrix}$$

## Formalization: Handling the Division

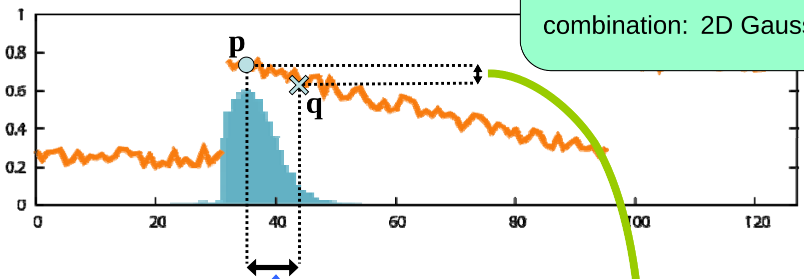
$$\begin{pmatrix} W_{\mathbf{p}}^{\mathrm{bf}} I_{\mathbf{p}}^{\mathrm{bf}} \\ W_{\mathbf{p}}^{\mathrm{bf}} \end{pmatrix} = \sum_{\mathbf{q} \in \mathcal{S}} G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\, G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|) \begin{pmatrix} W_{\mathbf{q}} I_{\mathbf{q}} \\ W_{\mathbf{q}} \end{pmatrix} \quad \text{with } W_{\mathbf{q}}=1$$

- Similar to homogeneous coordinates in projective space
- Division delayed until the end
- Next step: Adding a dimension to make a convolution appear

## Link with Linear Filtering
### 2. Introducing a Convolution

space: 1D Gaussian
× range: 1D Gaussian

combination: 2D Gaussian

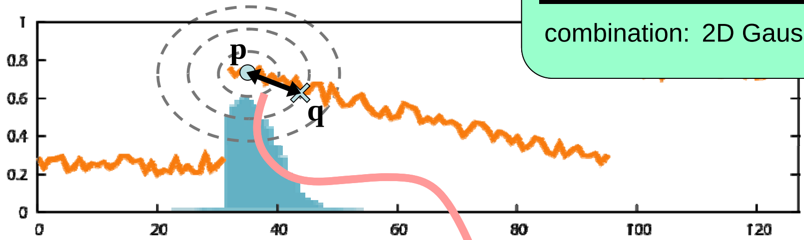



$$\begin{pmatrix} W_{\mathbf{p}}^{\mathrm{bf}} I_{\mathbf{p}}^{\mathrm{bf}} \\ W_{\mathbf{p}}^{\mathrm{bf}} \end{pmatrix} = \sum_{\mathbf{q} \in \mathcal{S}} \underbrace{G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)}_{\text{space}}\, \underbrace{G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)}_{\text{range}} \begin{pmatrix} W_{\mathbf{q}} I_{\mathbf{q}} \\ W_{\mathbf{q}} \end{pmatrix}$$

## Link with Linear Filtering
### 2. Introducing a Convolution

space: 1D Gaussian
× range: 1D Gaussian

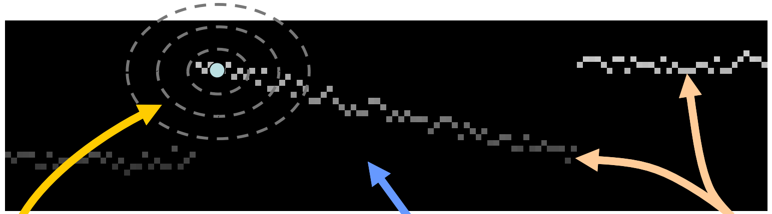
combination: 2D Gaussian




$$\begin{pmatrix} W_{\mathbf{p}}^{\mathrm{bf}} I_{\mathbf{p}}^{\mathrm{bf}} \\ W_{\mathbf{p}}^{\mathrm{bf}} \end{pmatrix} = \sum_{\mathbf{q} \in \mathcal{S}} \underbrace{G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)\, G_{\sigma_r}(|I_{\mathbf{p}} - I_{\mathbf{q}}|)}_{\text{space x range}} \begin{pmatrix} W_{\mathbf{q}} I_{\mathbf{q}} \\ W_{\mathbf{q}} \end{pmatrix}$$

Corresponds to a 3D Gaussian on a 2D image.

## Link with Linear Filtering
### 2. Introducing a Convolution



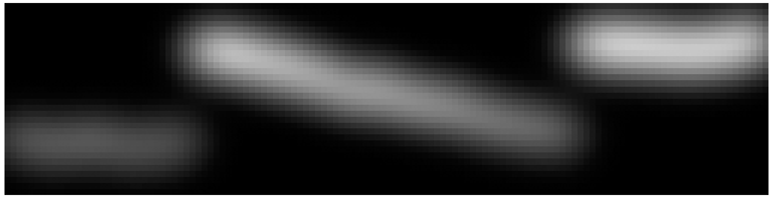
sum all values

black = zero

$$\begin{pmatrix} W_{\mathbf{p}}^{\mathrm{bf}} I_{\mathbf{p}}^{\mathrm{bf}} \\ W_{\mathbf{p}}^{\mathrm{bf}} \end{pmatrix} = \sum_{(\mathbf{q},\zeta) \in \mathcal{S} \times \mathcal{R}} \text{space-range Gaussian} \begin{pmatrix} W_{\mathbf{q}} I_{\mathbf{q}} \\ W_{\mathbf{q}} \end{pmatrix}$$

sum all values multiplied by kernel ⇨ convolution

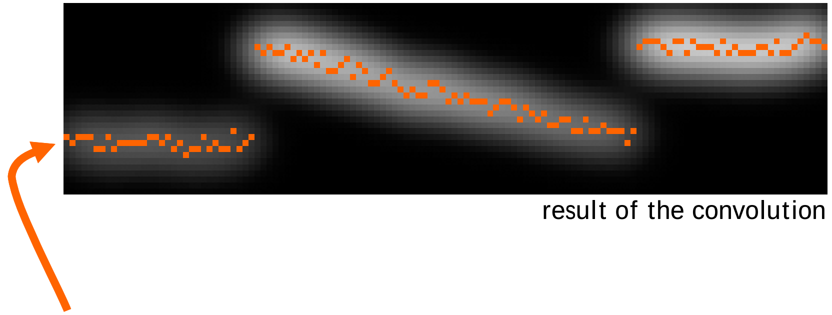
## Link with Linear Filtering
### 2. Introducing a Convolution



result of the convolution

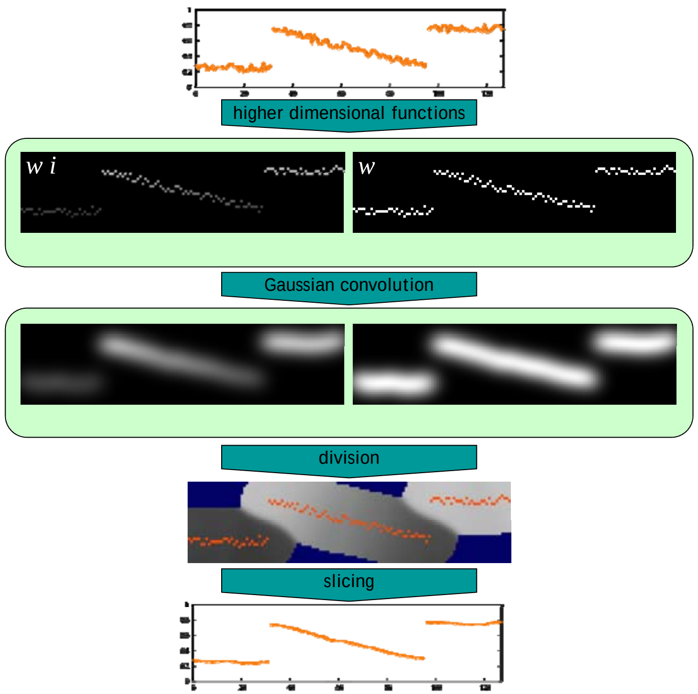
$$\begin{pmatrix} W^{\mathrm{bf}}_{\mathbf{p}}\, I^{\mathrm{bf}}_{\mathbf{p}} \\ W^{\mathrm{bf}}_{\mathbf{p}} \end{pmatrix} = \sum_{(\mathbf{q},\zeta)\in\mathcal{S}\times\mathcal{R}} \text{space-range Gaussian} \begin{pmatrix} W_{\mathbf{q}}\, I_{\mathbf{q}} \\ W_{\mathbf{q}} \end{pmatrix}$$

## Link with Linear Filtering
### 2. Introducing a Convolution



result of the convolution

$$\begin{pmatrix} W^{\mathrm{bf}}_{\mathbf{p}}\, I^{\mathrm{bf}}_{\mathbf{p}} \\ W^{\mathrm{bf}}_{\mathbf{p}} \end{pmatrix} = \sum_{(\mathbf{q},\zeta)\in\mathcal{S}\times\mathcal{R}} \text{space-range Gaussian} \begin{pmatrix} W_{\mathbf{q}}\, I_{\mathbf{q}} \\ W_{\mathbf{q}} \end{pmatrix}$$



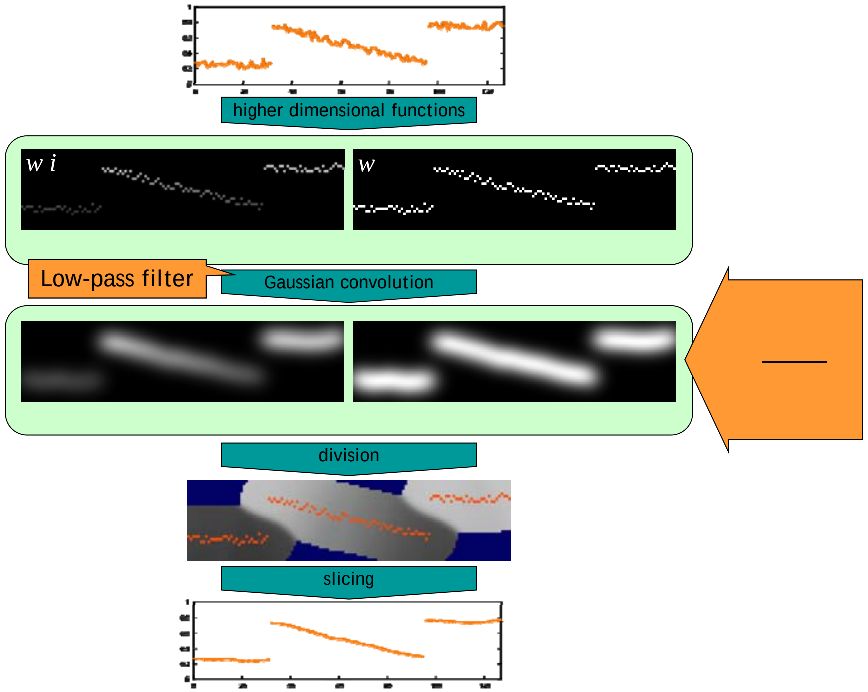

## Reformulation: Summary

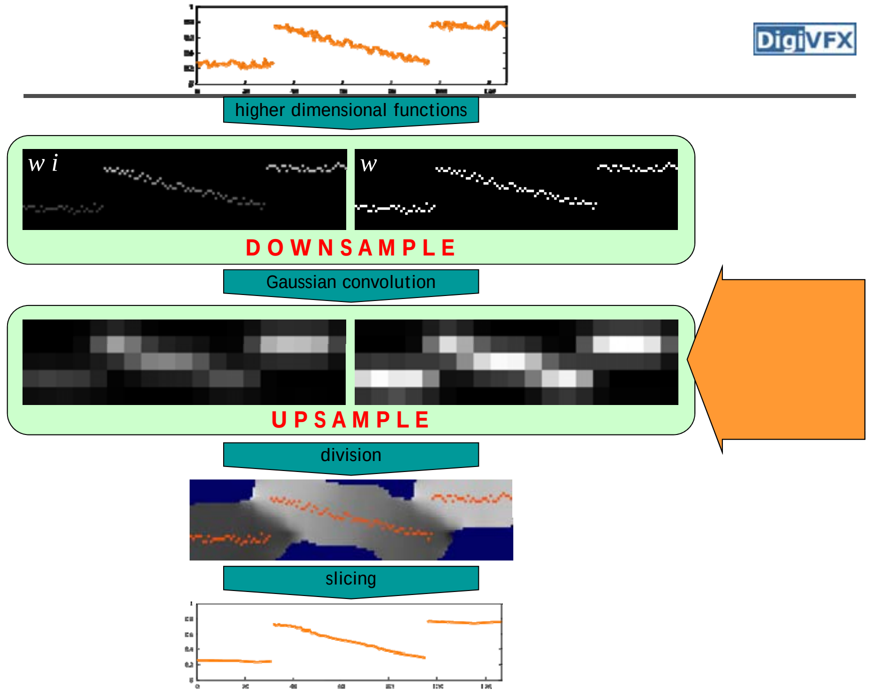
linear: $(w^{\mathrm{bf}}\, i^{\mathrm{bf}}, w^{\mathrm{bf}}) = g_{\sigma_s,\sigma_r} \otimes (wi, w)$

nonlinear: $I^{\mathrm{bf}}_{\mathbf{p}} = \dfrac{w^{\mathrm{bf}}(\mathbf{p}, I_{\mathbf{p}})\; i^{\mathrm{bf}}(\mathbf{p}, I_{\mathbf{p}})}{w^{\mathrm{bf}}(\mathbf{p}, I_{\mathbf{p}})}$

1. Convolution in higher dimension
   - expensive but well understood (linear, FFT, etc)
2. Division and slicing
   - nonlinear but simple and pixel-wise

**Exact reformulation**



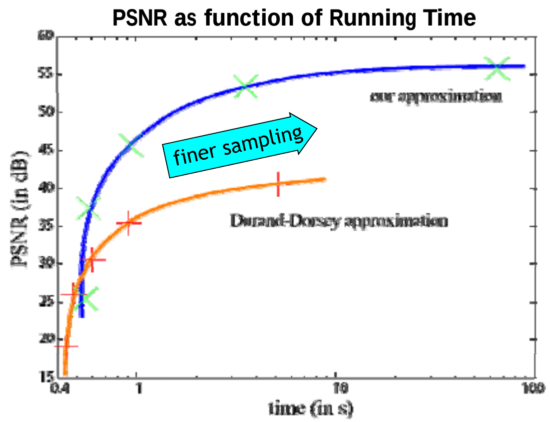




## Fast Convolution by Downsampling

- Downsampling cuts frequencies above Nyquist limit
  - Less data to process
  - But induces error
- Evaluation of the approximation
  - Precision versus running time
  - Visual accuracy

## Accuracy versus Running Time

- Finer sampling increases accuracy.
- More precise than previous work.

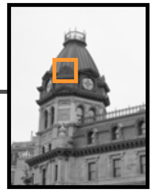



Digital photograph 1200 × 1600

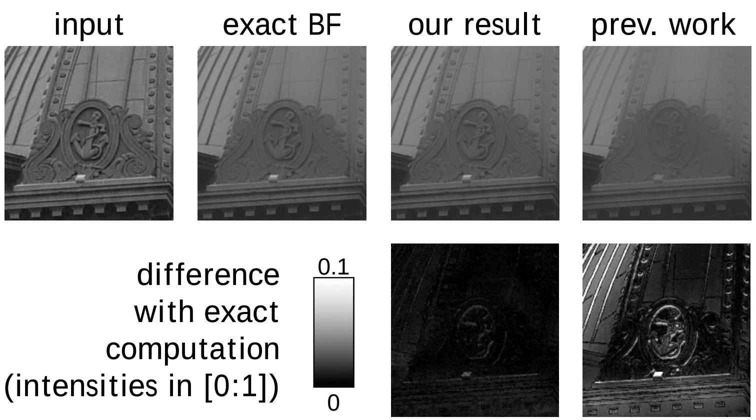
Straightforward implementation is over 10 minutes.

## Visual Results

- Comparison with previous work [Durand 02]
  - running time = 1s for both techniques



1200 × 1600




## Conclusions

**higher dimension ⇨ "better" computation**

### Practical gain

- Interactive running time
- Visually similar results
- Simple to code (100 lines)

### Theoretical gain

- Link with linear filters
- Separation linear/nonlinear
- Signal processing framework

# Two-scale Tone Management for Photographic Look


Soonmin Bae, Sylvain Paris, and Frédo Durand

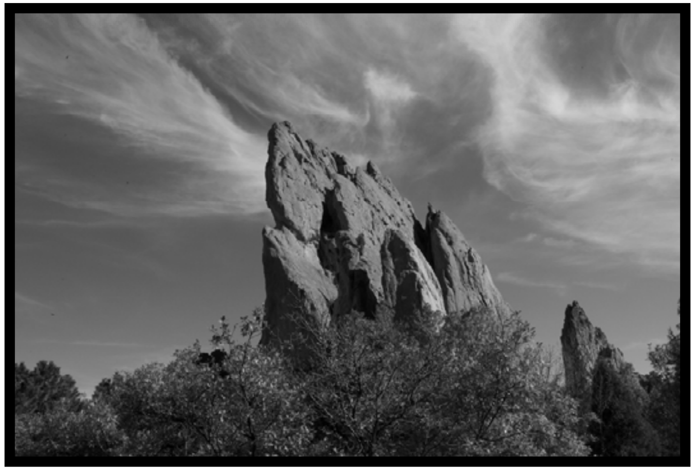
MIT CSAIL


SIGGRAPH2006

## Ansel Adams

Ansel Adams, *Clearing Winter Storm*

## An Amateur Photographer



## A Variety of Looks

## Goals

- Control over photographic look
- Transfer “look” from a model photo

For example,

we want  with the look of 

## Aspects of Photographic Look

- Subject choice
- Framing and composition

➔ Specified by input photos

Input

- Tone distribution and contrast

➔Modified based on model photos

Model

## Tonal Aspects of Look

Ansel Adams

Kenro Izu

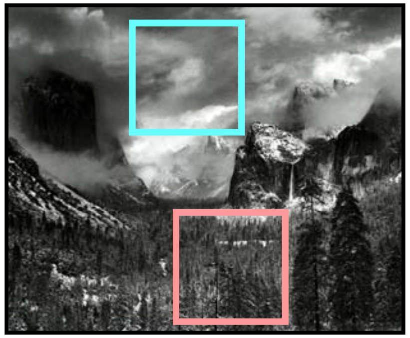
## Tonal aspects of Look - Global Contrast

Ansel Adams

Kenro Izu

**High Global Contrast** **Low Global Contrast**

## Tonal aspects of Look - Local Contrast

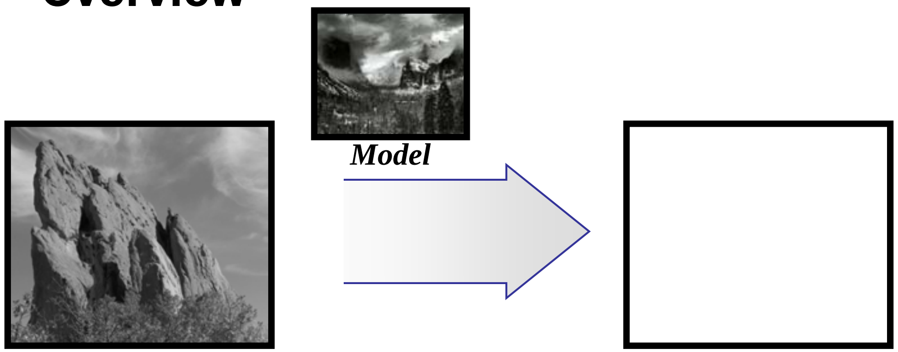


Ansel Adams

Kenro Izu

**Variable amount of texture** **Texture everywhere**

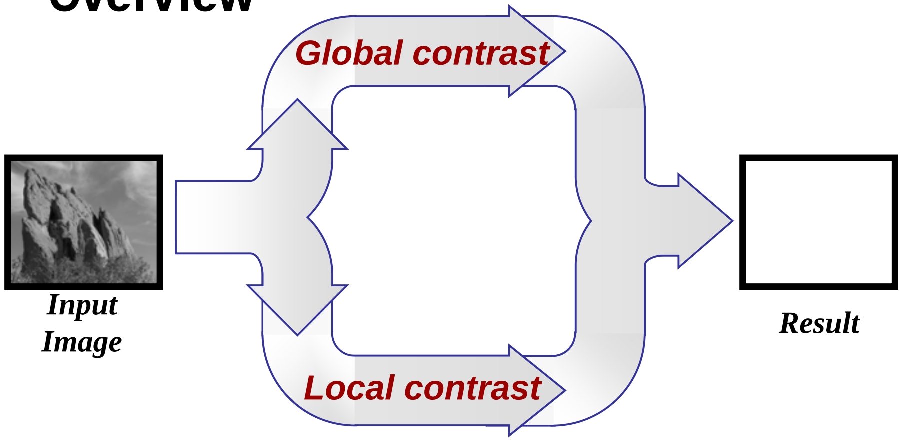
## Overview




*Input Image* *Result*

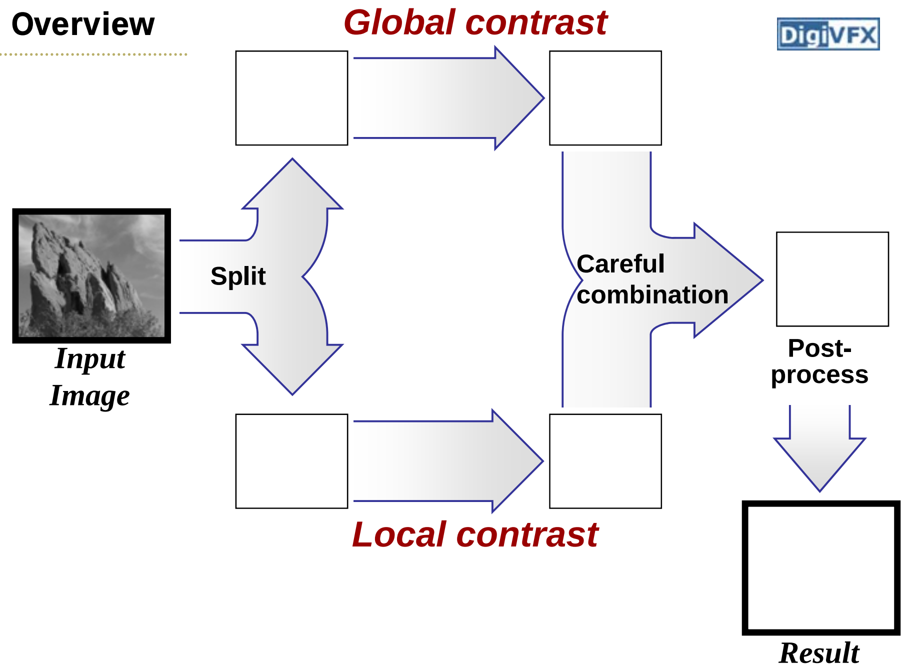
- Transfer look between photographs
  - Tonal aspects

# Overview

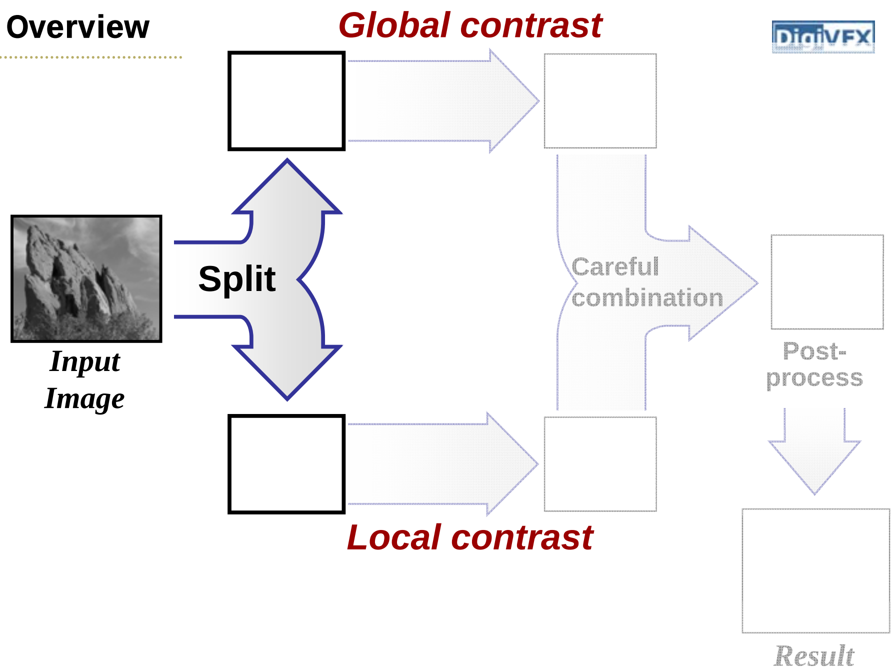



- Separate global and local contrast

## Overview



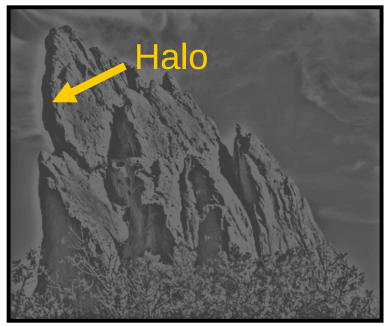

## Overview




# Split Global vs. Local Contrast

- Naïve decomposition: low vs. high frequency
  - Problem: introduce blur & halos


**Low frequency**
***Global contrast***




**High frequency**
***Local contrast***

## Bilateral Filter

- Edge-preserving smoothing [Tomasi 98]
- We build upon tone mapping [Durand 02]

After bilateral filtering
***Global contrast***

Residual after filtering
***Local contrast***

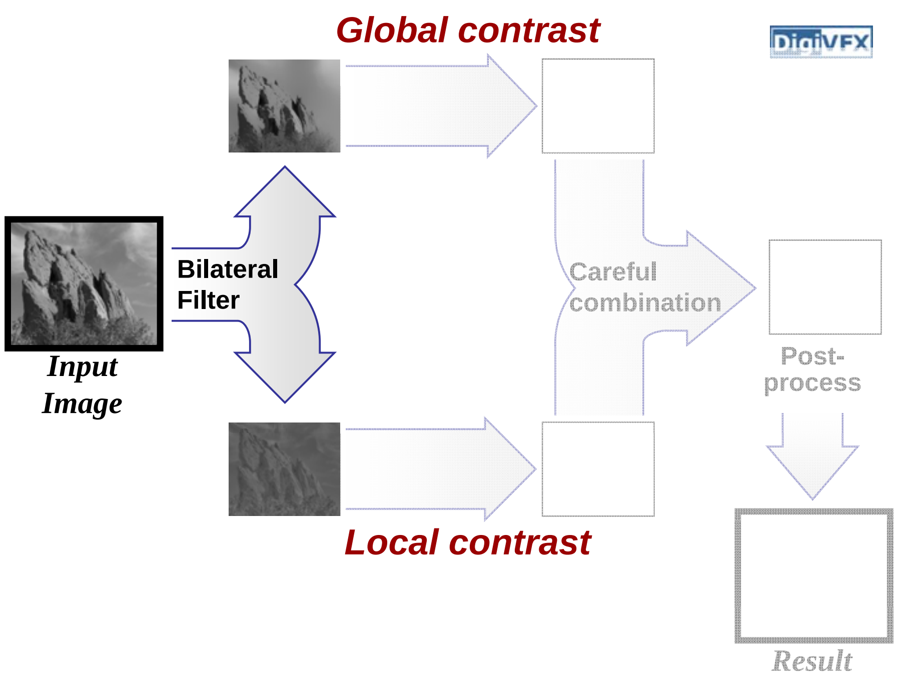

## Bilateral Filter

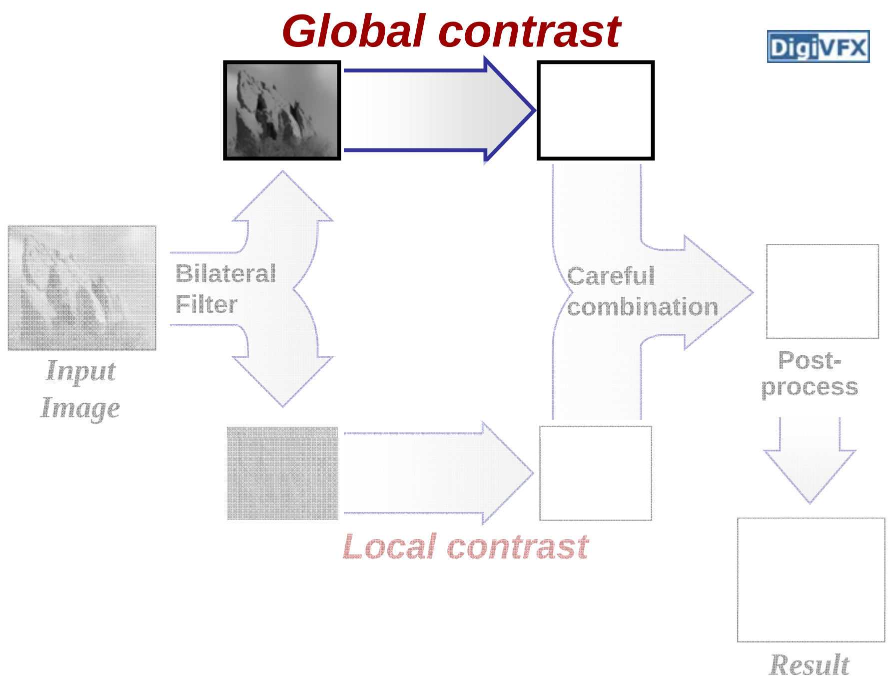
- Edge-preserving smoothing [Tomasi 98]
- We build upon tone mapping [Durand 02]



After bilateral filtering
***Global contrast***

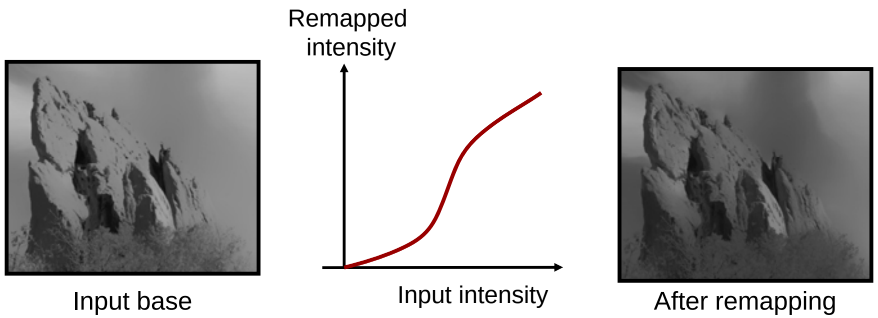

Residual after filtering
***Local contrast***



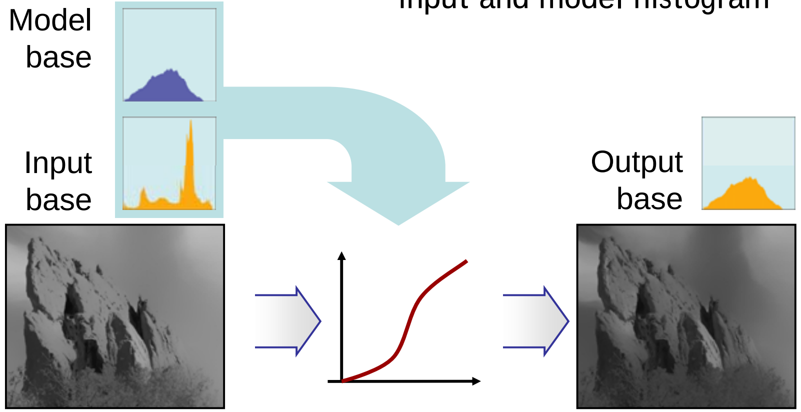
## Global Contrast

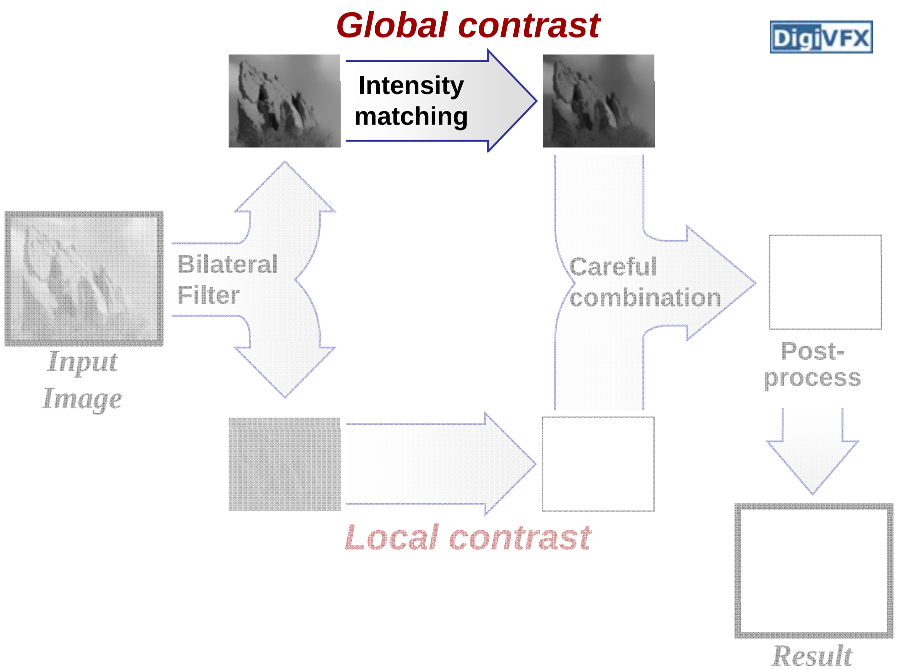
- Intensity remapping of base layer

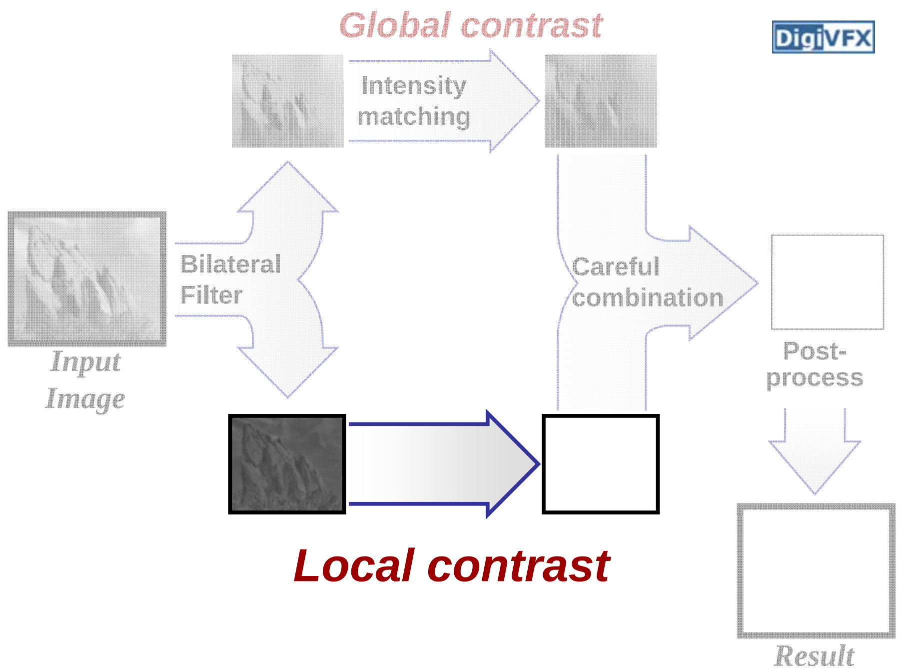



## Global Contrast (Model Transfer)

- Histogram matching
  - Remapping function given input and model histogram



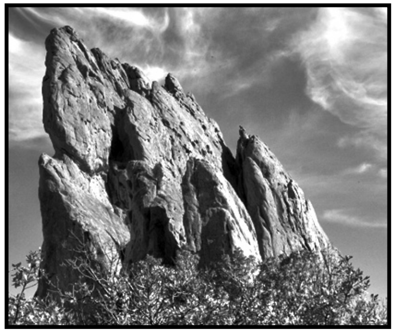



## Local Contrast: Detail Layer

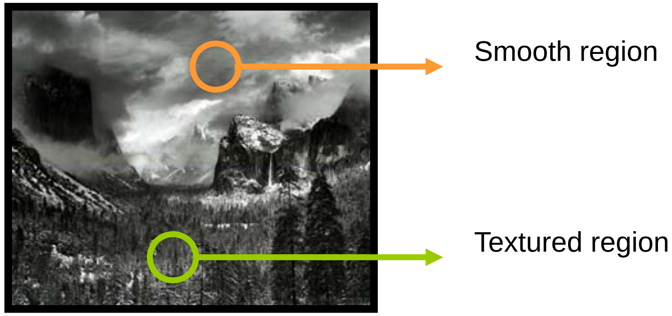
- Uniform control:
  - Multiply all values in the detail layer

Input



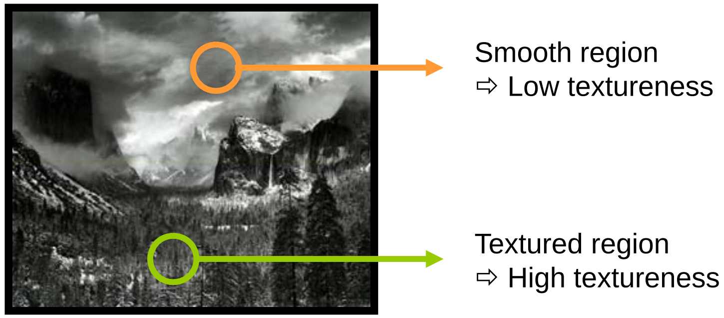
Base + 3 × Detail

## The amount of local contrast is not uniform

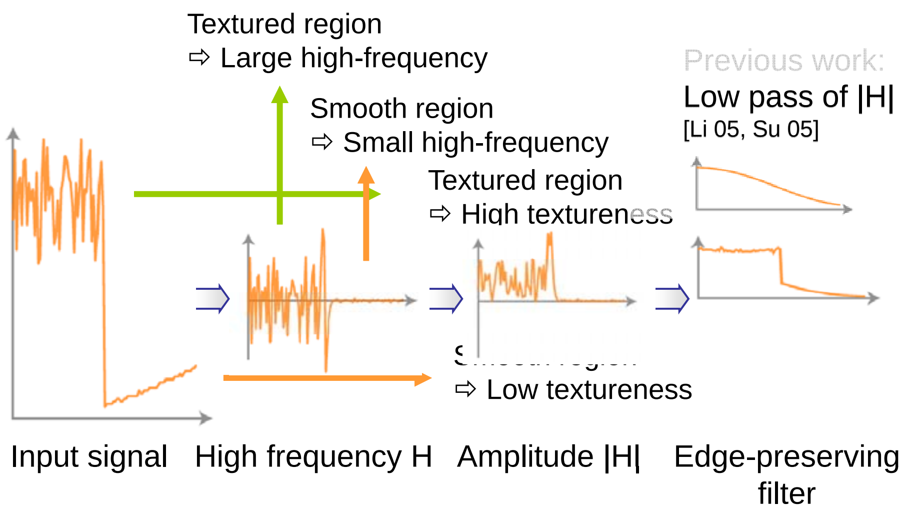



## Local Contrast Variation

- We define "textureness": amount of local contrast
  - at each pixel based on surrounding region

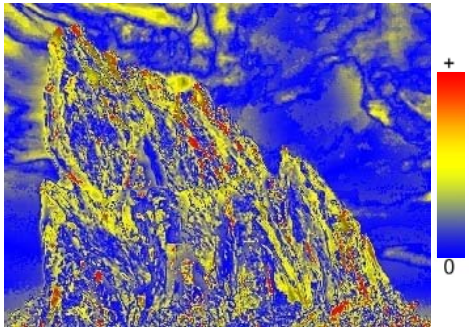



## "Textureness": 1D Example



## Textureness

Input

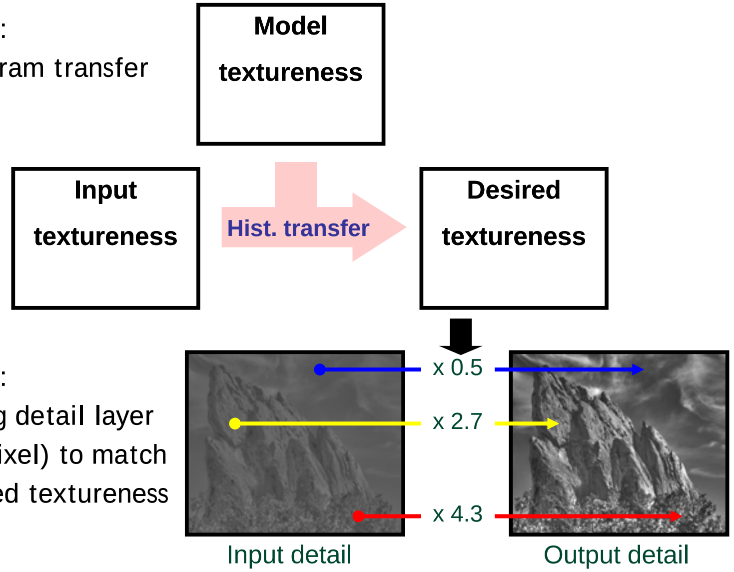


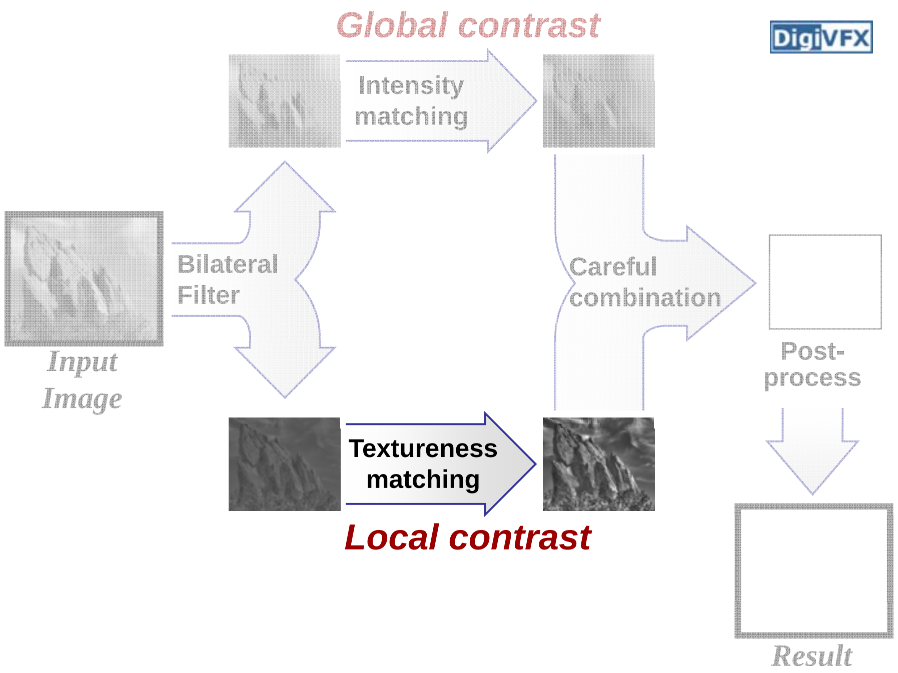

Textureness

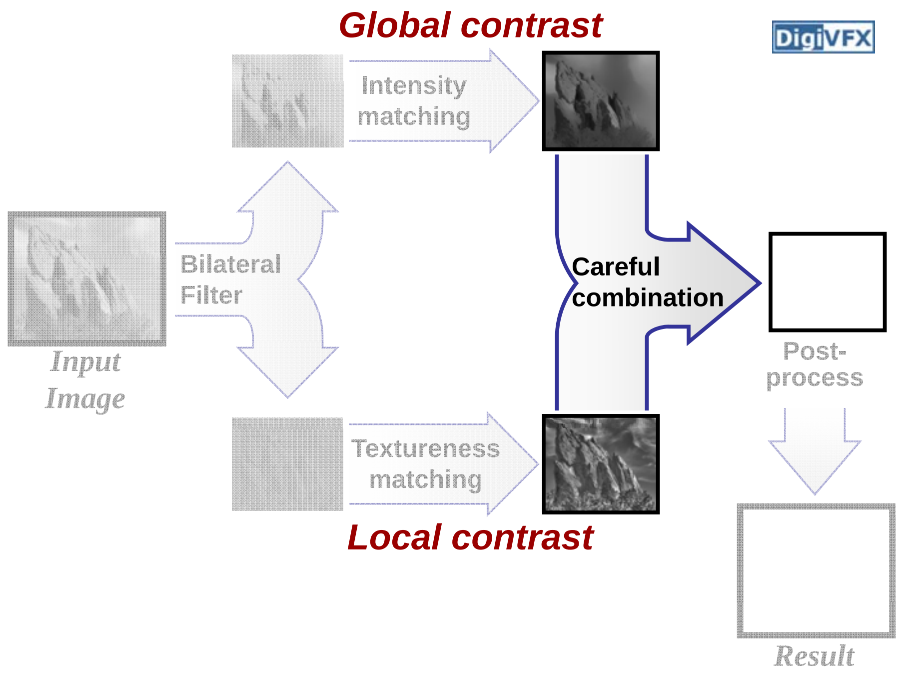
## Textureness Transfer

Step 1:
Histogram transfer

Step 2:
Scaling detail layer (per pixel) to match desired textureness



# A Non Perfect Result

- Decoupled and large modifications (up to 6x)
  ➔Limited defects may appear

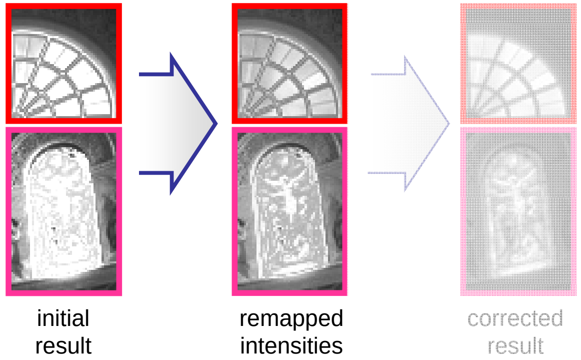
input (HDR)

result after
global and local adjustments

# Intensity Remapping

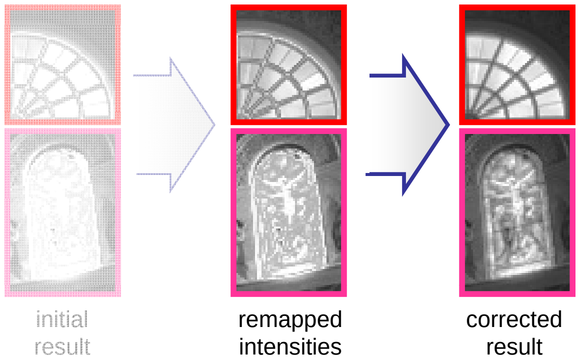
- Some intensities may be outside displayable range.

➔ Compress histogram to fit visible range.




# Preserving Details

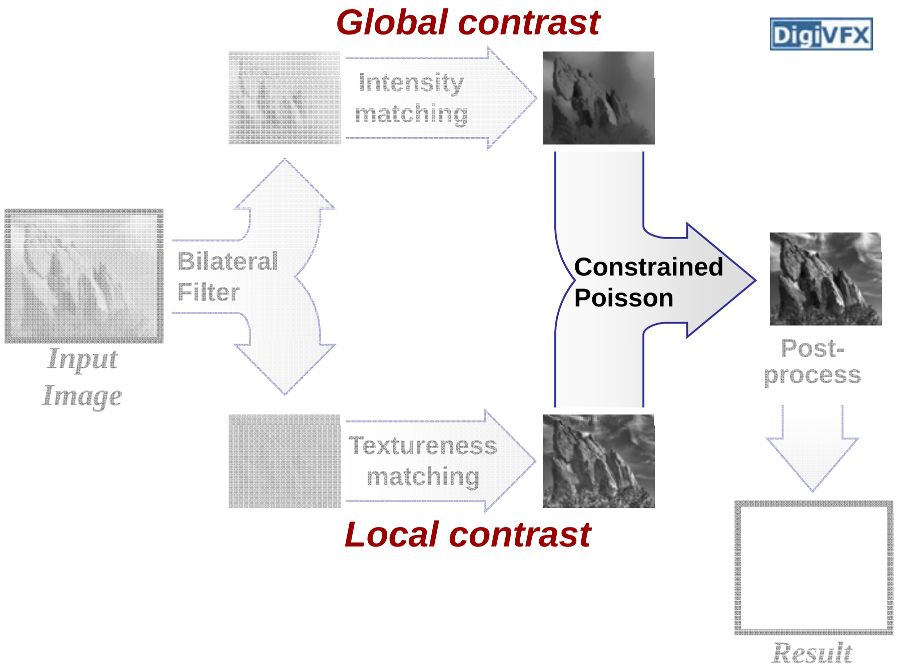
1. In the **gradient domain**:
   - Compare gradient amplitudes of input and current
   - Prevent extreme reduction & extreme increase
2. Solve the **Poisson equation**.

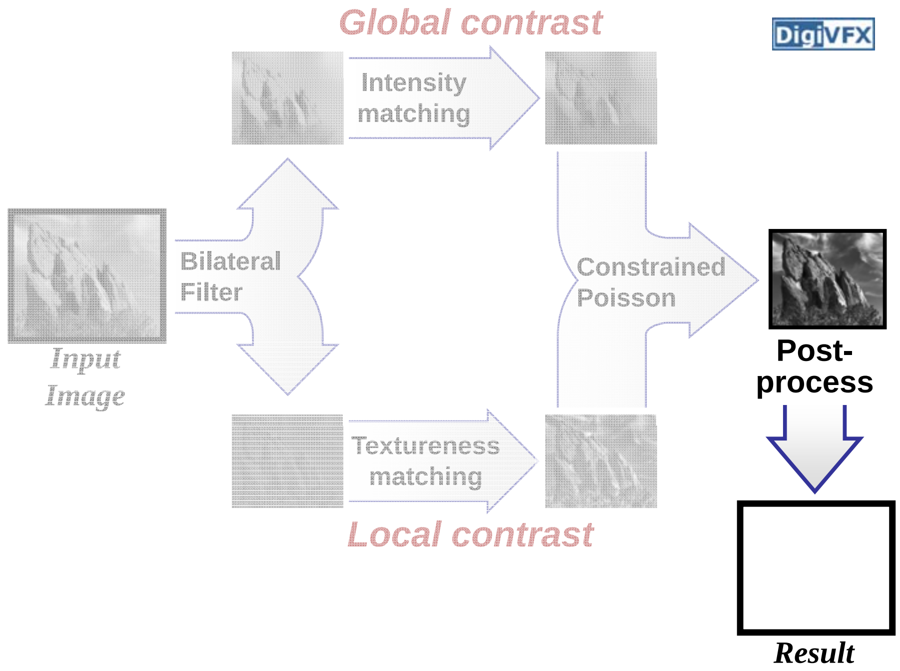



# Effect of Detail Preservation

uncorrected result

corrected result



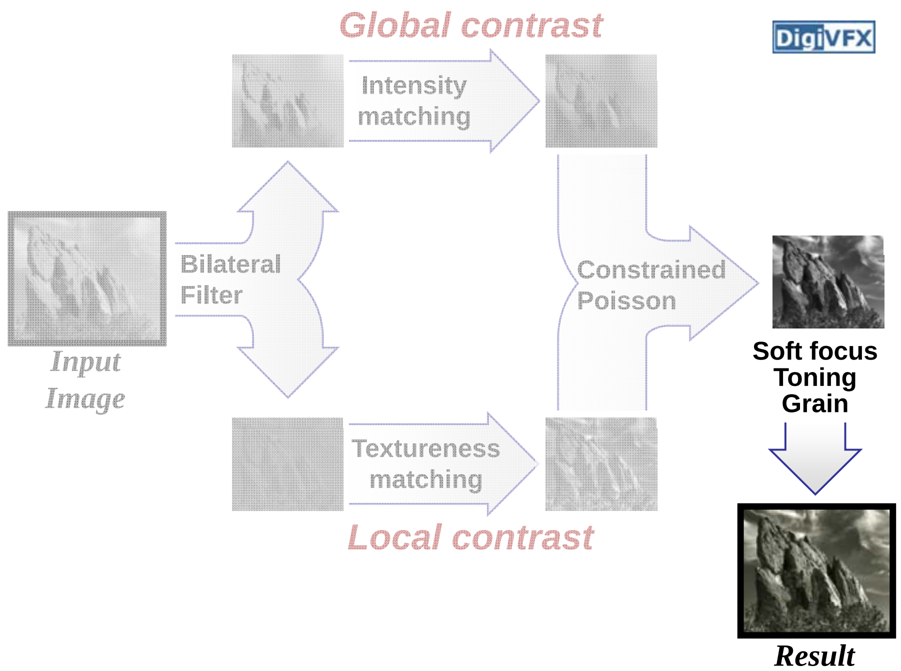

## Additional Effects

model

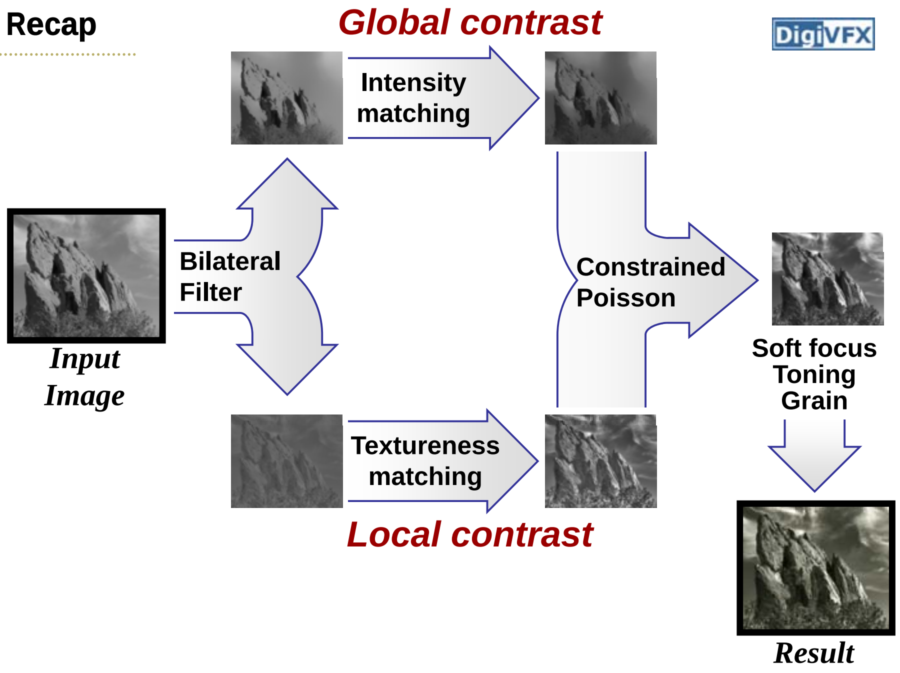
- **Soft focus** (high frequency manipulation)
- **Film grain** (texture synthesis [Heeger 95])
- **Color toning** (chrominance = $f$ (luminance))

before effects

after effects



## Recap




## Results

User provides input and model photographs.

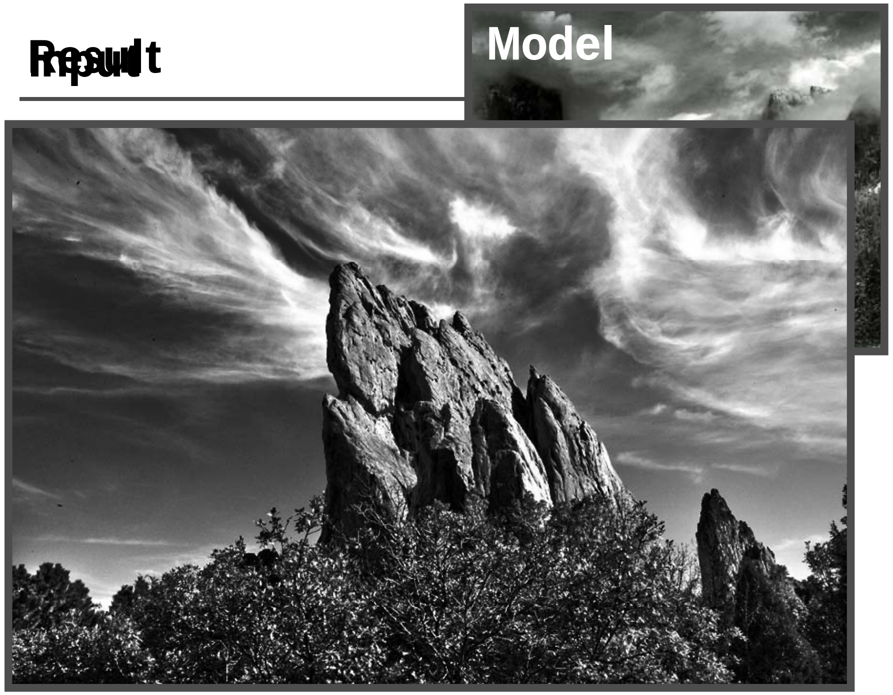
➔ Our system **automatically** produces the result.

Running times:

- 6 seconds for 1 MPixel or less
- 23 seconds for 4 MPixels
- multi-grid Poisson solver and fast bilateral filter [Paris 06]

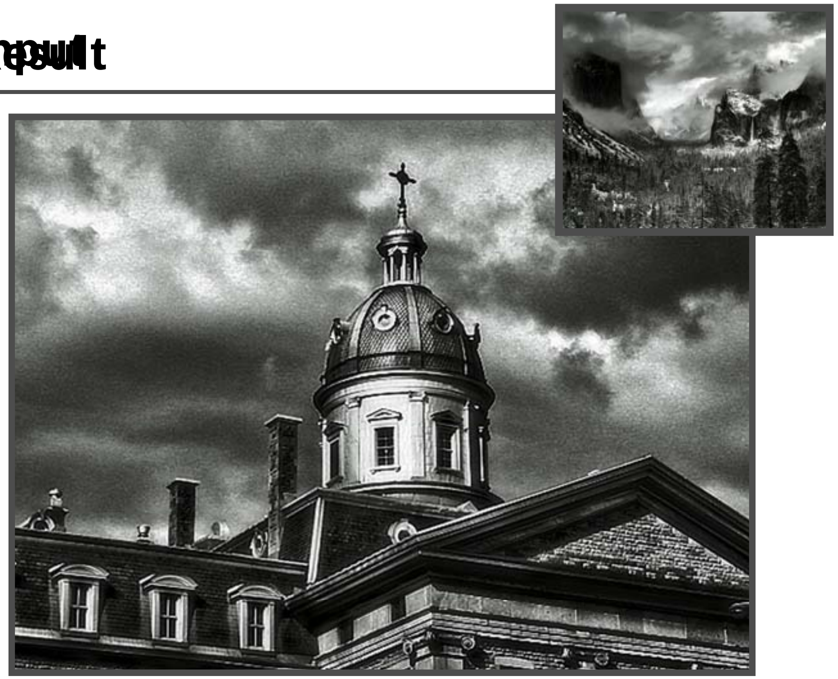
## Result

Input

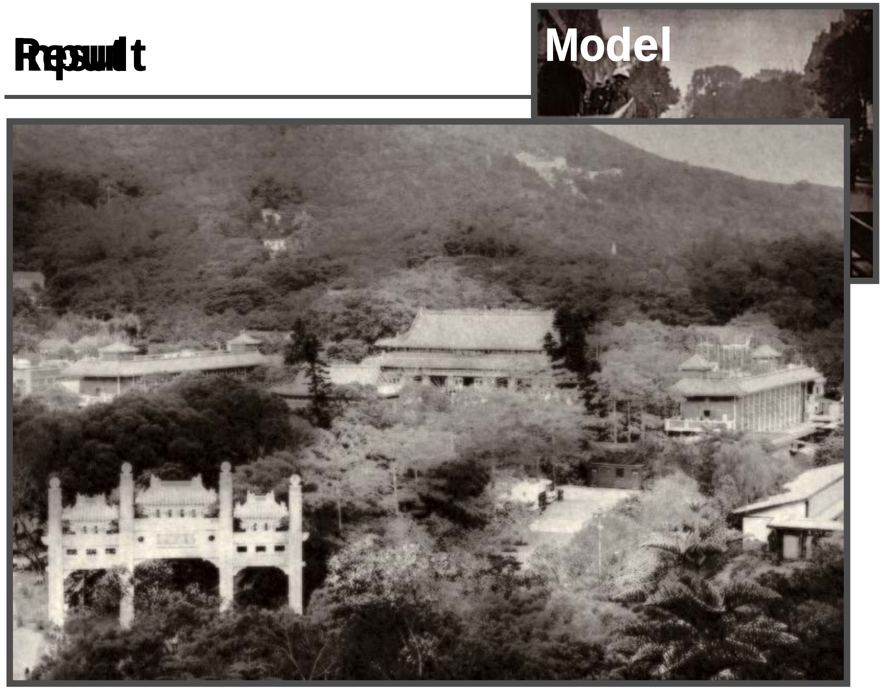



## Result

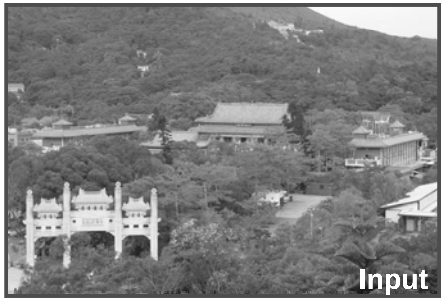
Input



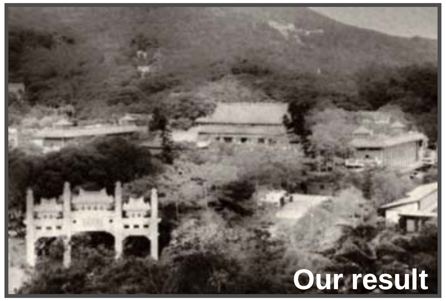
## Result




## Comparison with Naïve Histogram Matching






Local contrast, sharpness unfaithful

## Comparison with Naïve Histogram Matching





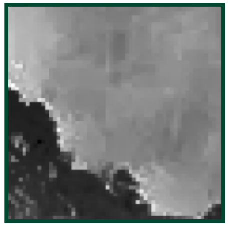
Local contrast too low

## Color Images

- **Lab color space: modify only luminance**


## Limitations

- Noise and JPEG artifacts
  - amplified defects



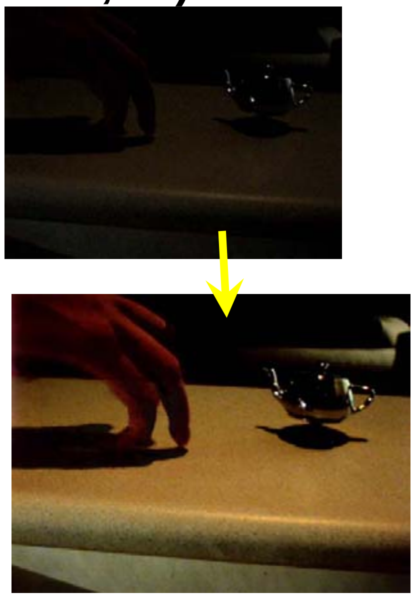
- Can lead to unexpected results if the image content is too different from the model
  - Portraits, in particular, can suffer

## Conclusions

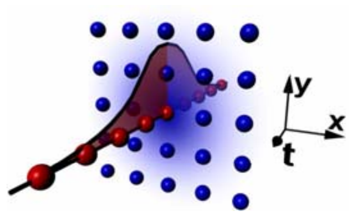
- Transfer "look" from a model photo
- Two-scale tone management
  - Global and local contrast
  - New edge-preserving textureness
  - Constrained Poisson reconstruction
  - Additional effects

## Video Enhancement Using Per Pixel Exposures (Bennett, 06)

From this video:



ASTA: ***A**daptive*
***S**patio-*
***T**emporal*
***A**ccumulation Filter*




## Joint bilateral filtering

$$J_p = \frac{1}{k_p} \sum_{q \in \Omega} I_q \, f(||p-q||) \, g(||I_p - I_q||)$$

$$J_p = \frac{1}{k_p} \sum_{q \in \Omega} I_q \, f(||p-q||) \, g(||\tilde{I}_p - \tilde{I}_q||)$$

## Flash / No-Flash Photo Improvement (Petschnigg04) (Eisemann04)

DigiVFX

Merge best features: warm, cozy candle light (no-flash)
low-noise, detailed flash image

## Overview

DigiVFX

Basic approach of both flash/noflash papers

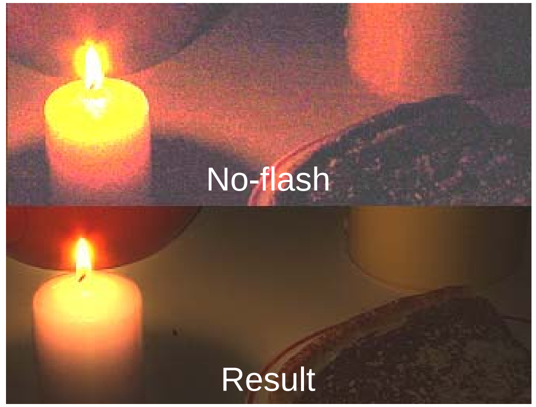
Remove noise + details from image A,

Keep as image A Lighting

-----------------------

Obtain noise-free details from image B,

Discard Image B Lighting




## Petschnigg:

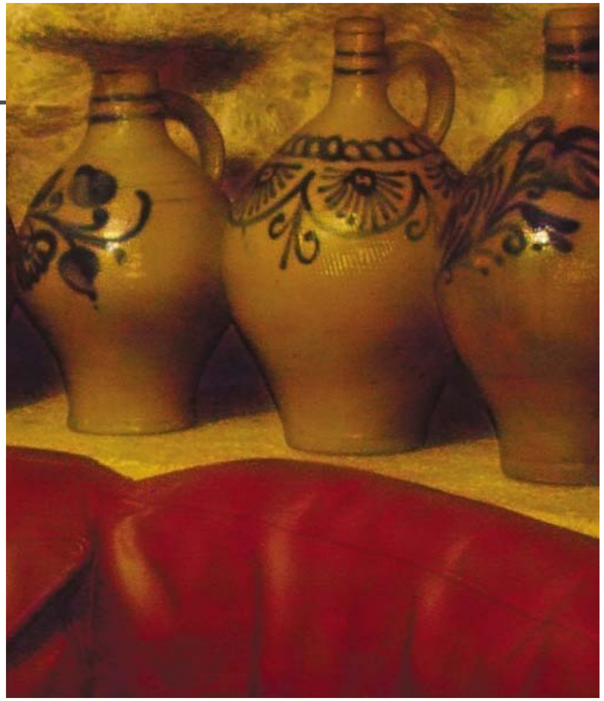
- Flash

## Petschnigg:

- No Flash,

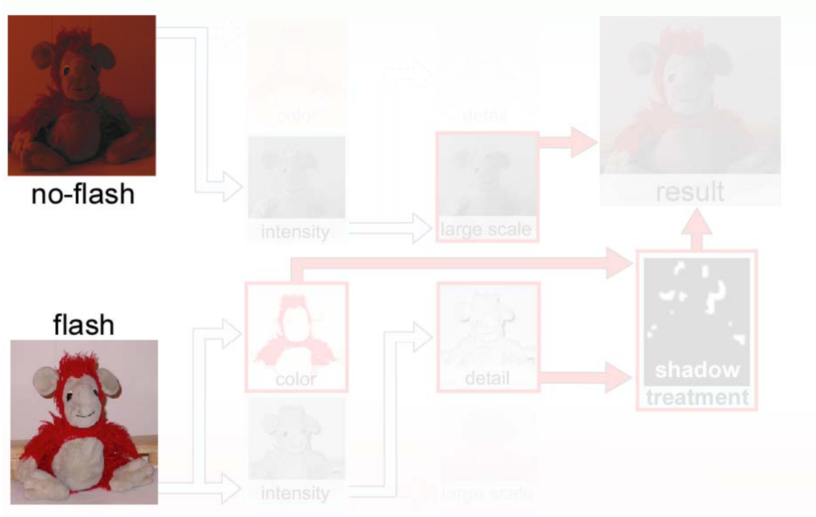
## Petschnigg:

- Result



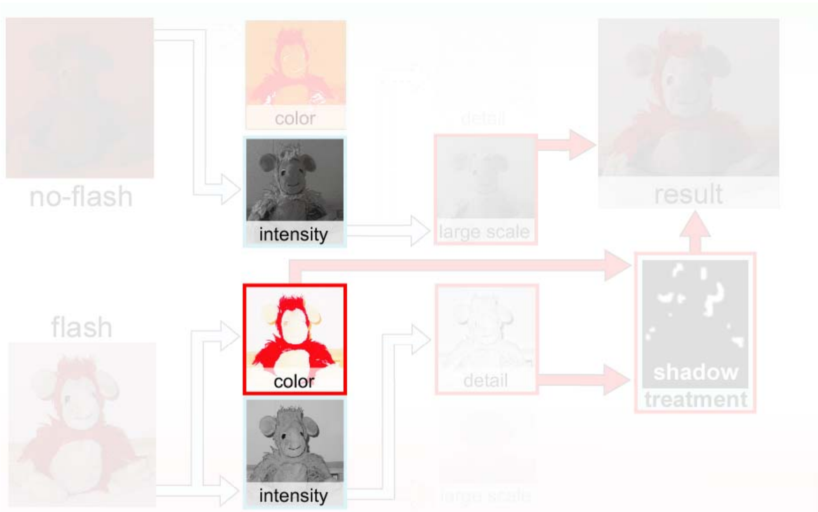
## Our Approach

Registration



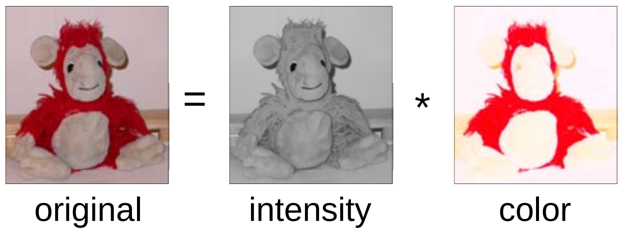

## Our Approach

Decomposition




## Decomposition

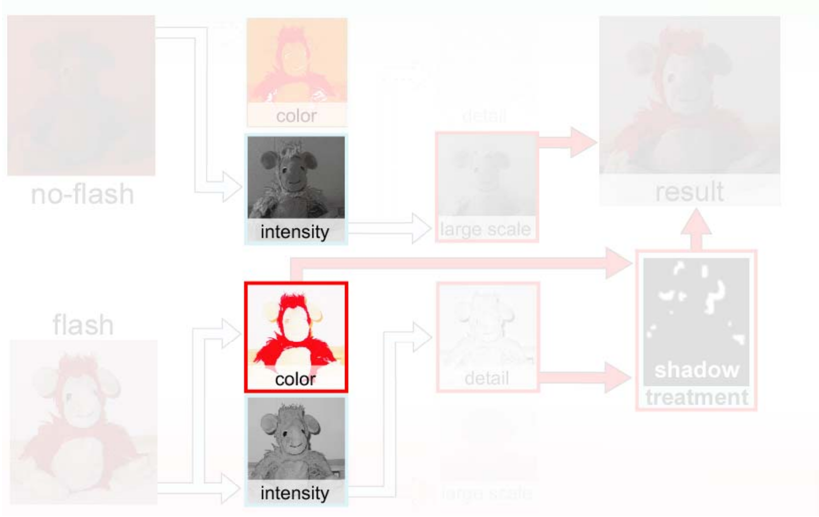
Color / Intensity:



# Our Approach

DigiVFX

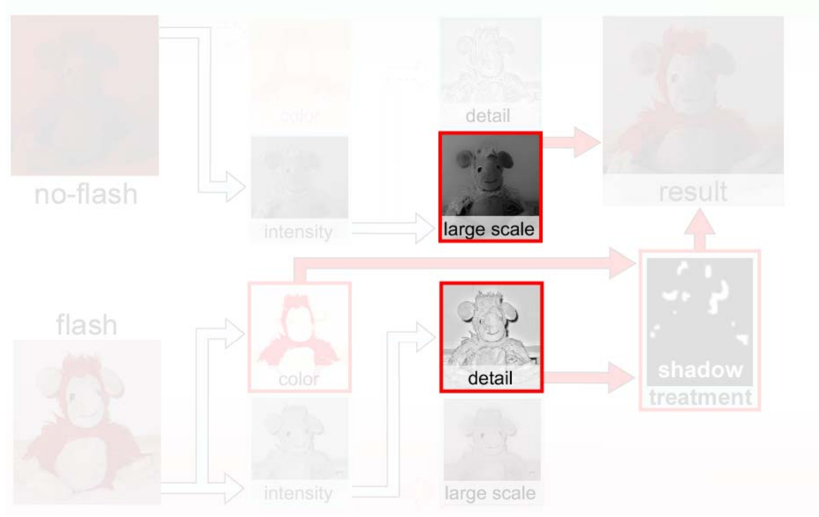
Decomposition




# Our Approach

DigiVFX

Decoupling




# Decoupling

DigiVFX

- Lighting : Large-scale variation
- Texture : Small-scale variation

Lighting

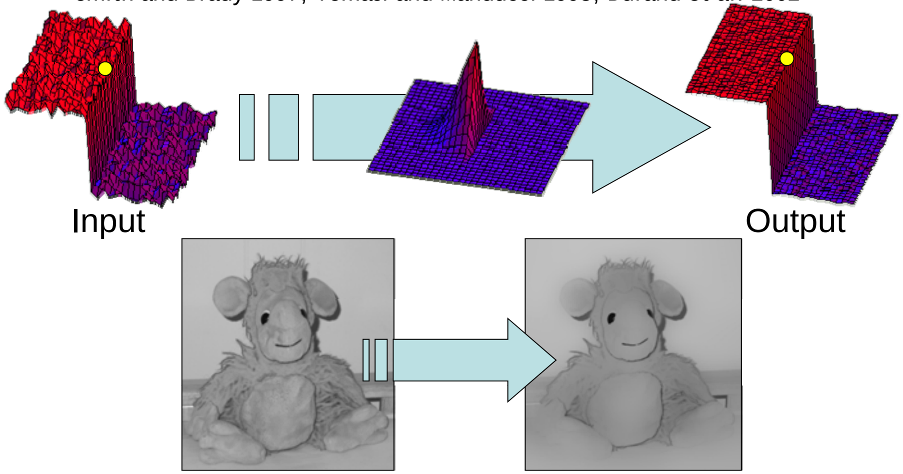
Texture

# Large-scale Layer

DigiVFX

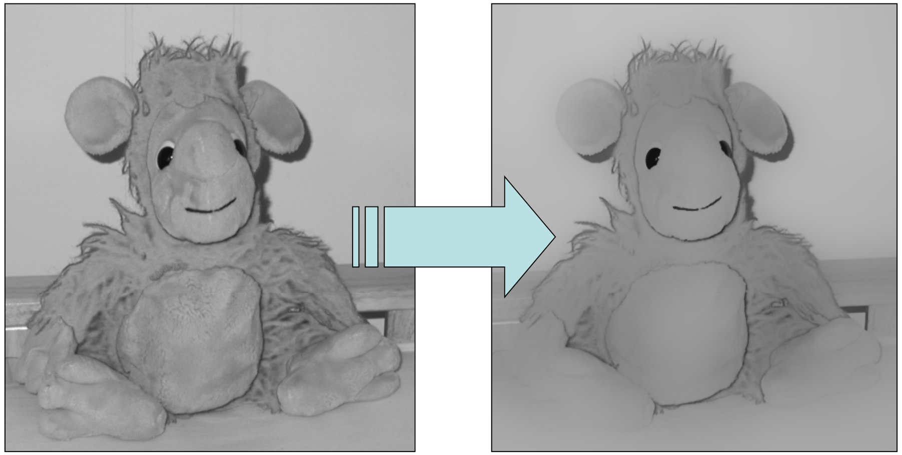
- Bilateral filter – edge preserving filter

Smith and Brady 1997; Tomasi and Manducci 1998; Durand et al. 2002



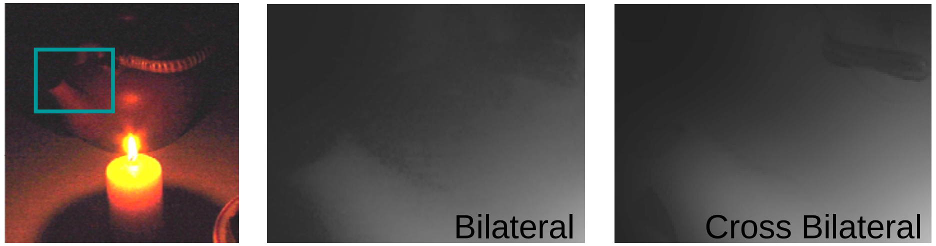
## Large-scale Layer

- Bilateral filter

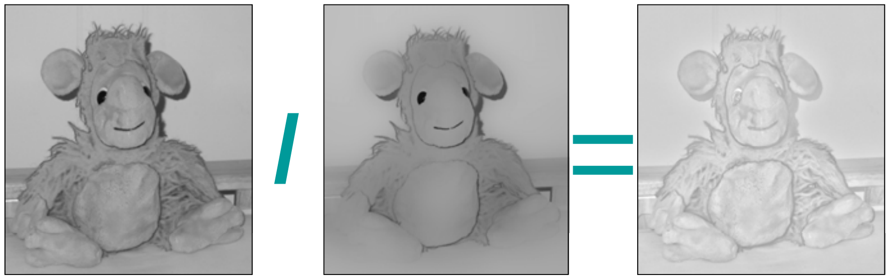


## Cross Bilateral Filter

- Similar to joint bilateral filter by Petschnigg et al.
- When no-flash image is too noisy
- Borrow similarity from flash image
  - ➢ edge stopping from flash image




## Detail Layer




Intensity    Large-scale    Detail

Recombination: Large scale * Detail = Intensity

## Recombination


Large-scale No-flash    Detail Flash    Intensity Result

Recombination: Large scale * Detail = Intensity

## Recombination

shadows

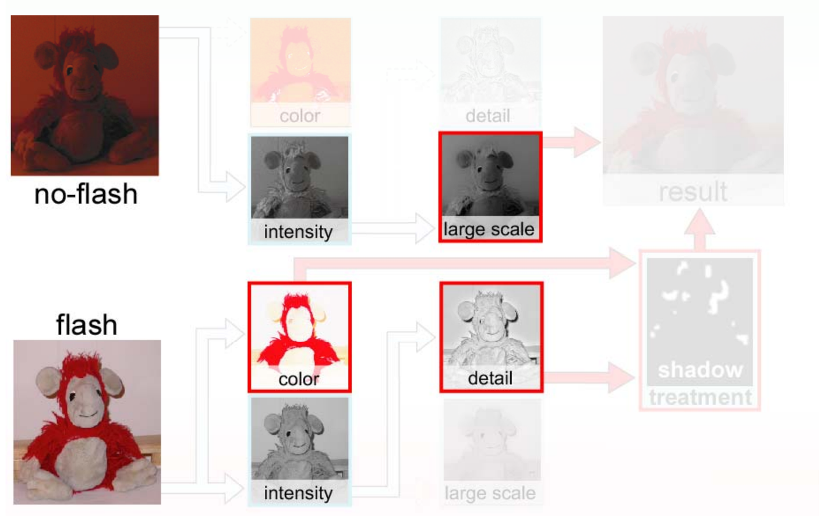

Intensity Result

Color Flash

Result

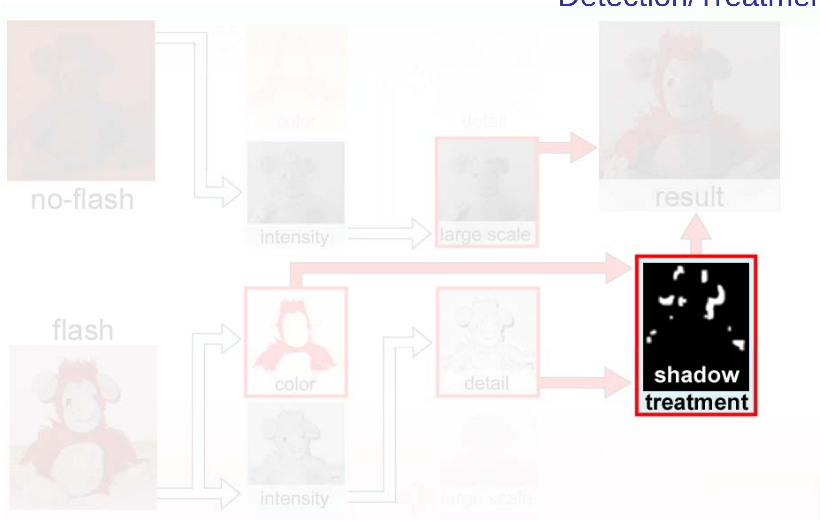
Recombination: Intensity * Color = Original

## Our Approach




## Our Approach

Shadow Detection/Treatment




## Results

No-flash

Flash

## Joint bilateral upsampling

DigiVFX

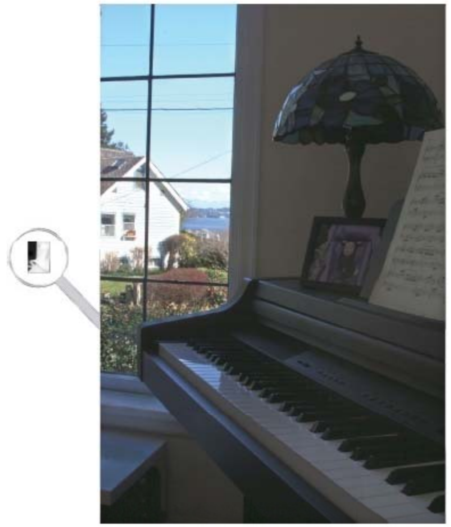
$$J_p = \frac{1}{k_p} \sum_{q \in \Omega} I_q \, f(||p-q||) \, g(||I_p - I_q||)$$

$$J_p = \frac{1}{k_p} \sum_{q \in \Omega} I_q \, f(||p-q||) \, g(||\tilde{I}_p - \tilde{I}_q||)$$

$$\tilde{S}_p = \frac{1}{k_p} \sum_{q_\downarrow \in \Omega} S_{q_\downarrow} \, f(||p_\downarrow - q_\downarrow||) \, g(||\tilde{I}_p - \tilde{I}_q||)$$

## Joint bilateral upsampling

DigiVFX



Upsampled Result

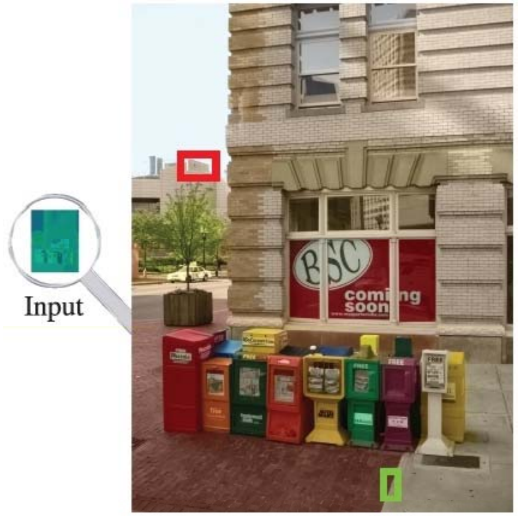
## Joint bilateral upsampling

DigiVFX

Nearest Neighbor | Bicubic | Gaussian | Joint Bilateral | Ground Truth

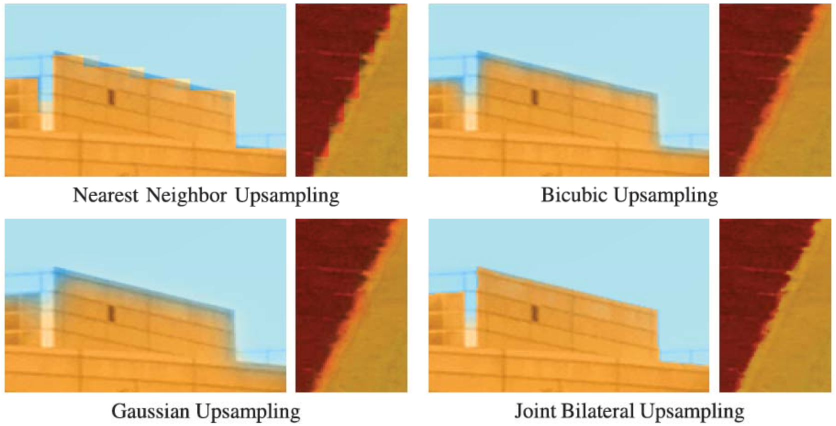
## Joint bilateral upsampling

DigiVFX




Upsampled Result

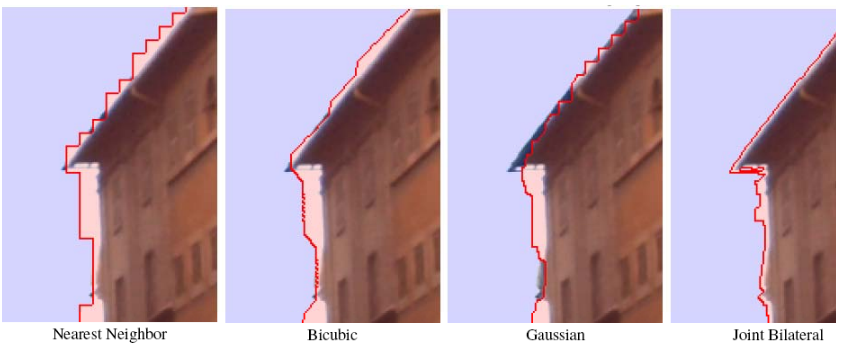
# Joint bilateral upsampling




# Joint bilateral upsampling


Input Images

# Joint bilateral upsampling




# Joint bilateral upsampling

Upsampled Result